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Impacts and opportunities of new mobilities for the electrical system

Rémi Lauvergne

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Impacts and opportunities of new mobilities for the electrical system

*Impacts et opportunités des nouvelles mobilités pour le
système électrique*

Thèse de doctorat de l'université Paris-Saclay

École doctorale n° 573 : matériaux, systèmes, usages (INTERFACES)
Spécialité de doctorat : Ingénierie des systèmes complexes
Graduate School : Science de l'ingénierie et des systèmes. Référent : CentraleSupélec

Thèse préparée dans l'unité de recherche **Laboratoire Génie Industriel (Université Paris-Saclay, CentraleSupélec)**, sous la direction de **Pascal DA COSTA**, Professeur et la co-direction de **Yannick PEREZ**, Professeur

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1 - Chapter 1: General Introduction

1.1 Climate change and its implications on transport and energy sectors

Since the first publication of the Intergovernmental Panel on Climate Change (IPCC) report in 1992 (IPCC, 1992), this organization has become one, if not the most, important scientific research group. Its latest report published to date (IPCC, 2022) informs us through its 3 working groups of the causes of global warming, its risks as well as possible solutions to mitigate it. The key message is that global warming is caused by anthropogenic greenhouse gases emissions and appears to be a threat to our civilization in the next years and decades.

A major challenge in the coming years is therefore to limit those anthropogenic emissions of greenhouse gases, mainly carbon dioxide (CO₂), as well as methane, nitrogen oxides and others, which have skyrocketed since the second half of the 19th century, as illustrated in Figure 1.1.

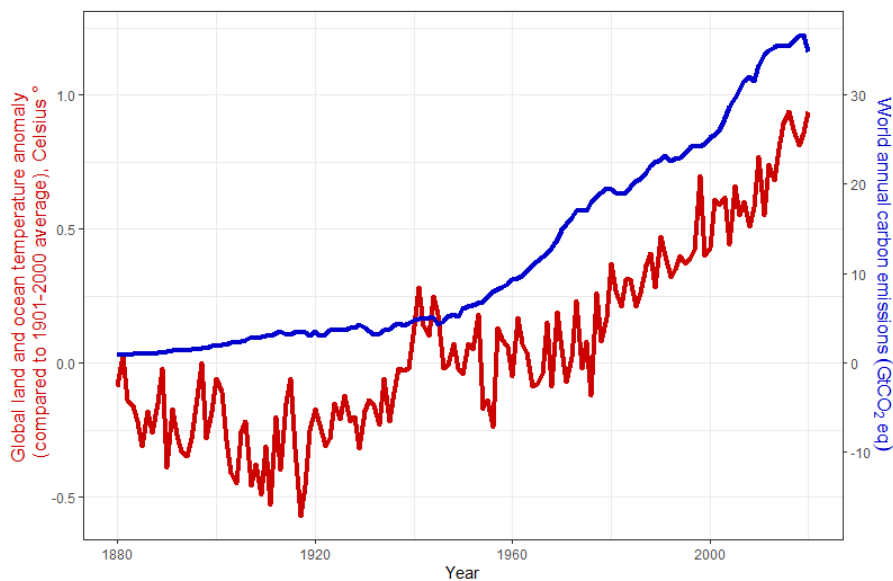


Figure 1.1: Evolution of carbon emissions and global temperature average from 1880 to 2020 (temperature data from NOAA (2022), and carbon emission data from Ritchie et al. (2020))

Thus, many research efforts attempt to propose or evaluate more domain- or object-specific solutions to reduce carbon emissions, and this work is located within this context, at the intersection of the transportation and electricity generation sectors.

We illustrate in Figure 1.2 the distribution of carbon emissions by sector, for France and the European Union (EU). It appears that in France, transport and electricity generation account for respectively 30% and 5% of the total national emissions. In the EU, these numbers reach 32% for electricity generation (whose decarbonization is less advanced than in France, see section 1.3.1) and 29% for the transport sector.

There are different ways to account for carbon emissions: direct emissions on the territory, emissions from life cycle analysis (LCA), carbon balance by evaluating imports and exports (Matthews et al., 2008). In this manuscript, the "emissions" expressed will be, unless otherwise stated, direct emissions on the territory, also known as "Scope 1 emissions", which are yet the most commonly used carbon accounting methodology in public and accessible data and less sensitive to structural assumptions. However, LCA seems much more accurate in taking into account the total carbon impact of consumption.

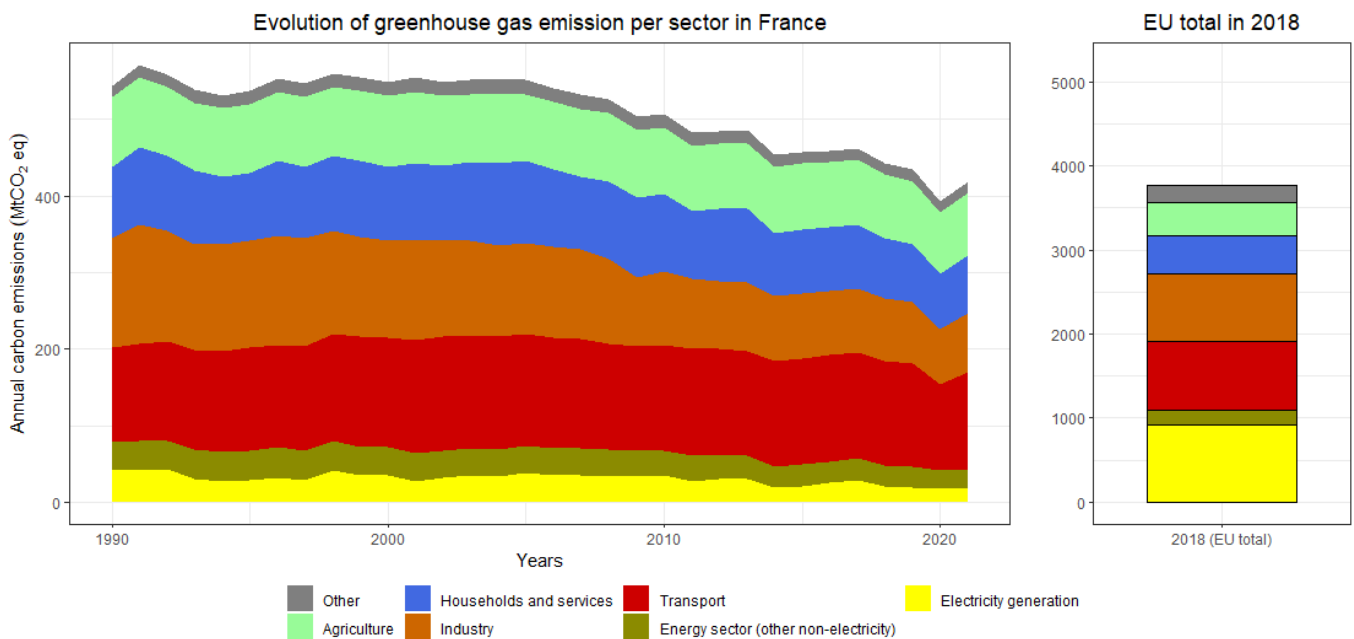


Figure 1.2: Evolution of carbon emissions per sector in France since 1990, compared to the EU total emission per sector (data from SDES (2021))

The following of this introductory Chapter is divided as follows: first, the prospects for decarbonization of transport are described, with a focus on vehicle electrification, then the evolution of electricity generation mixes is explained, before detailing the interaction between those two sectors, and finally the research questions and the structure of this thesis are presented.

1.2 Evolutions in the field of transport to reduce fossil fuel propulsion

1.2.1 A brief historical context of transport in France

The transport sector has developed strongly during the 20th century, with the advent of oil extraction. Indeed, until the 18th century, the majority of trips were made by foot or horse (and bikes from mid 19th century), with a large proportion of individuals never travelling more than a few kilometers away from their homes. Merger (1987) reviews the main historical literature about transport development in France. First, the road and rail networks began to be built in the second half of the 18th century, until a larger development spread over the whole territory in the first part of the 20th century, before finally a more massive plan of road renovation and construction in the 1970s. The advent of petroleum allowed the development of much faster, more efficient, and less expensive modes of transport. At first, individual vehicles were reserved for the wealthy, but their use grew steadily during the 20th century. Although electric propulsion for road vehicles has existed since the middle of the 19th century (Burton, 2013), it proved to be uncompetitive throughout the 20th century, compared to thermal vehicles.

The transport sector is often divided into two large blocks: passenger transport and freight transport. First, regarding passenger transport, in 1990, 77% of French households owned a car, of which 26% owned two or more (INSEE, 2020). These figures have increased in the last 30 years to reach respectively 84% and 36% of households in 2020. Moreover, INSEE (2020) estimates that only 2.7% of French people do not own a car due to lack of financial means (against 6.8% in the EU). The survey INSEE (2017) also allows the comparison of household expenditures by sector and over time. This survey informs us that the average share of expenditure devoted to transport in France has remained stable between 2004 and 2019, at around 15% of total expenditures. That is, even though the price of oil has been on a (chaotic) upward trend since 1990, the thermal car has remained affordable for most French households, as expenditures have yet increased correspondingly.

This increase in the ownership and use of individual vehicles appears to be similar for most developing countries, while very few countries have begun a transition towards a reduction in distances traveled (IEA, 2019).

Second, the transport of goods has also continuously grown, in parallel with globalization. In France, goods transport totals 362 Gt.km/year within the territory, 89% by road trucks, and only 9% of rail freight and 2% of waterway transport (SDES, 2021).

When focusing on the transport sector evolution in the last 30 years, the total final consumption in France was on a rising trend up to 2000 and then remained stable up to 2019 (SDES, 2019a). The associated carbon emissions of the transport sector are illustrated in Figure 1.3, which shows that emissions followed the same

trend as consumption, while slightly decreasing in the last 15 years¹. Significantly less carbon was emitted in 2020 and 2021, but the transport sector in those years was affected by the Covid-19 pandemic (Le Quéré et al., 2020), which makes those 2 years not representative of a strong shift towards decarbonization of the transport sector. Figure 1.3 also illustrates the targeted path of France’s SNBC (2019), which defines its baseline trajectory in order to reach net-zero carbon emissions in 2050. As studied by many in the literature, this trajectory requires breaking the trend observed in the last 30 years, both at the French and European level, either by technological shift (Rottoli et al., 2021), lifestyle changes (Costa et al., 2021) or a combination of policies (Haasz et al., 2018).

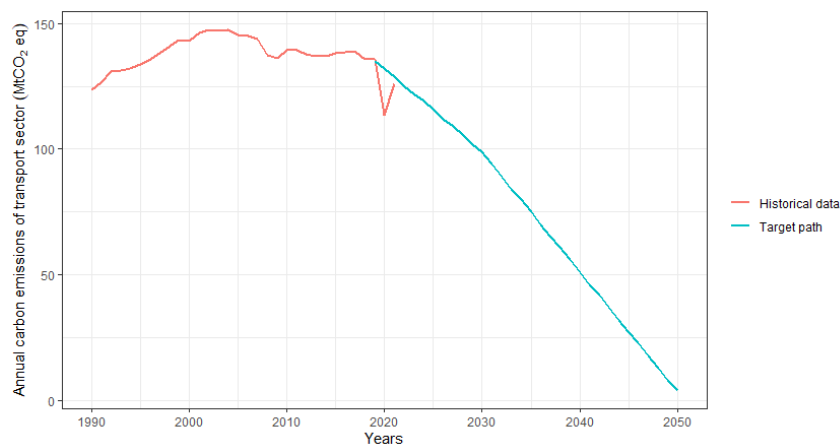


Figure 1.3: Evolution of the transport sector carbon emissions in France since 1990, and target path towards net-zero emission in 2050 (data from Citepa (2022))

To summarize this subsection, mobility in France in the last century has become widespread in the population, carbon intensive and multimodal even if a large majority of passenger transport is ensured by personal cars, and a majority of freight transport by trucks.

1.2.2 The potential for electrification of all major means of transport

When we divide the analysis made in the previous section per transport mode, it appears that individual vehicles, especially cars (which account for 97% of motorised distances travelled in individual vehicles, with less than 3% of two-wheeler use), stand for the largest share (80.5%) of distances travelled annually by passengers inside France (Arafer, 2019). The evolution since 1990 of those distances travelled per vehicle type is illustrated in Figure 1.4. Total annual distances

¹Most transport related data in this section, and more generally in the Chapter range up to 1990, which is the starting date of nearly all historical data easily available for France. For more detailed historical study of the transport sector in France (from 1960 and even before), see the work of Bigo (2020).

travelled have never noticeably decreased from a year to another in the last 30 years if we leave aside the year 2020 when distances travelled were significantly reduced because of Covid-19 lockdown. It is to be noted that other transport modes known as active mobility including cycling and electric scooters stand for less than 1% of distances travelled in 2019, so they are not included in Figure 1.4. As a result, individual vehicles account for the major part of the decarbonization effort to be made.

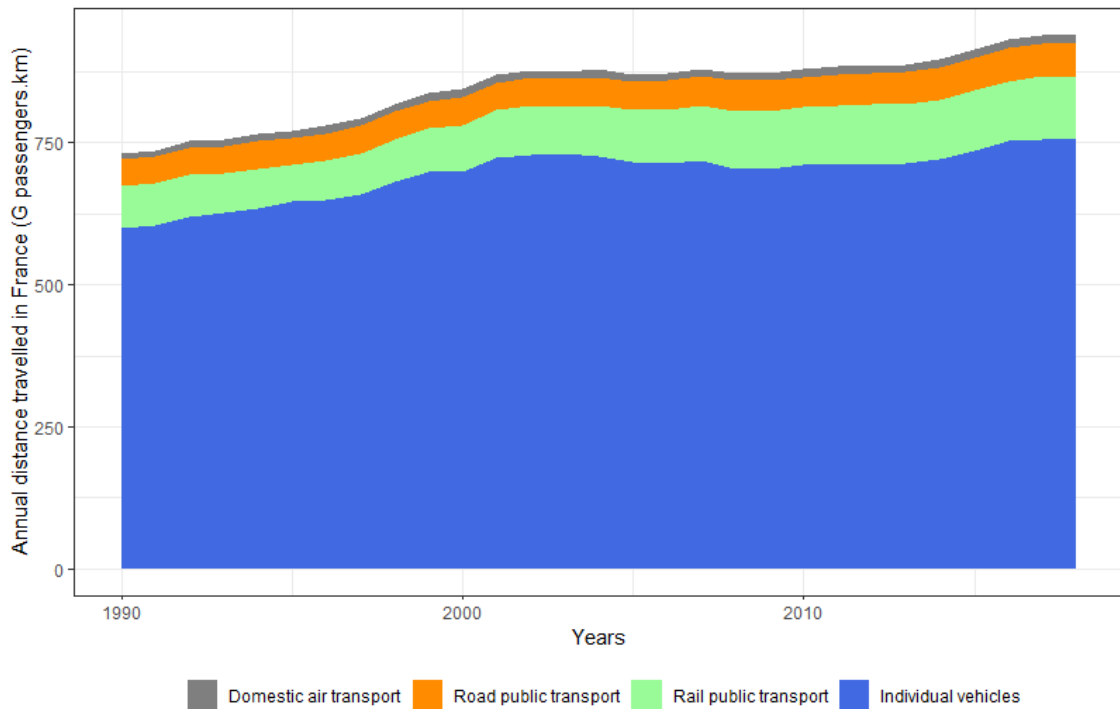


Figure 1.4: Evolution of the distances travelled per vehicle type in France (data from Arafer (2019))

The decarbonization of the transport sector relies on the five elements of the equation introduced by Kaya (1990), adapted for the transport sector by Bigo (2020) (among others). These five elements are total transport demand, modal shift, occupancy rate, energy efficiency and carbon intensity of energy. In this work, we study in more depth the energy efficiency and carbon intensity parameters, although all five are advisable to reduce the impact of the transport sector on climate change.

Regarding carbon intensity of energy for mobility purposes, electric vehicles (EVs) are currently seen as an opportunity to reduce greenhouse gases and other local polluting emissions of the transport sector, as an alternative to thermal vehicles relying on carbon intensive fuels. Recent events have also spotlighted the uncertainty surrounding the future of fossil fuel prices and strengthened resolve to press ahead with reducing oil dependency. Many governments are consequently incentivizing EV use, and some have even planned to ban the sale or

use of combustion-engine vehicles in the mid-term, by 2025 in Norway, by 2030 in Germany, the UK and the Netherlands, and by 2035 in France and at the EU level, for instance (Conway et al., 2021). Additionally other policy decisions such as bonus/penalty system depending on vehicle carbon emissions, taxes on carbon intensive fuels, urban toll systems (such as in London and Stockholm) or free parking and accesses to bus lanes for low-emission vehicles can serve to incentivize EV development. Furthermore, battery costs are expected to decrease in the coming decades², so EV total cost of ownership (TCO) are expected to match thermal vehicle's in the coming years. Therefore, the share of EVs in the transport sector is forecasted to surge in the next few years. The International Energy Agency's (IEA) EV30@30 scenario forecasts that half of all vehicle sales in Europe could be EVs by 2030 (IEA, 2019). This yearly issue by the IEA has become one of the key document assessing EV development perspectives.

Different types of EV propulsion and power storage are being developed, including: battery electric vehicles (BEVs) that exclusively use an electrochemical battery (with a capacity typically ranging from 20 kWh to 100 kWh for individual cars) to power an electric motor; plug-in hybrid electric vehicles (PHEVs) that have both an on-board electrical motor with electrochemical battery-pack storage and a combustion engine with a petrol tank; and fuel-cell electric vehicles (FCEVs) that carry an on-board hydrogen tank combined with fuel cells to power an on-board electrical motor. Other hybrid vehicles that cannot be plugged-in to charge their battery and whose only energy source is petrol, biogas or liquefied petroleum gas are outside of the scope of this work, as they do not interact with the power grid.

In addition to carbon emissions, other negative externalities related to the transportation sector are to be noted: nitrogen oxides (NOx) emissions, that cause respiratory diseases (César et al., 2015), particulate matter from road and brakes wear (Abu-Allaban et al., 2003) and noise (with its impacts on sleep and other health issues) (Bugliarello et al., 2014).

Electric vehicles contribute to the reduction of at least NOx and noise, particulate matter impact depending on vehicle mass and whereas eco-driving is considered or not. We observe either less brake wear thanks to regenerative braking (Paredes et al., 2013) or higher wear because of heavier vehicles (Oroumiyeh & Zhu, 2021).

In the following subsections, we detail the electrification potential and relevance of studying the transport modes that make up the sector.

Personal vehicles

To begin with, passenger cars are by far the most studied mode of transport in the academic literature on electric vehicles. Indeed, many scenarios predict a massive development in the next few years, between 40% and 78% of sales in Europe in

²However, recent events showed some unexpected rise in the price of lithium (Cai, 2022) linked to geopolitical events and a rising lithium demand (or potentially other resources) can threaten the veracity of this anticipated cost reduction

2030 in scenarios from IEA (2021b), up to 50% of the vehicle fleet electrified in France in 2035 according to RTE (2019) or around 50% of BEV and PHEV in the USA in the "SAFE" scenario, in 2030 (Conway et al., 2021). This is mainly due to the fact that some sources anticipate that total cost of ownership (TCO) of light electric vehicles will equal those of thermal vehicles in the next few years, due to the reduction in battery costs (Goldie-Scot & BloombergNEF, 2019; IEA, 2021b), along bans on thermal vehicle sales. Development is already well advanced in some parts of the world, notably Norway, which is the leading country with a 56% market share of BEVs in 2020 (IEA, 2021b).

The IEA currently identifies 5 main barriers to its development: insufficient charging infrastructure, not enough electric car models, too high purchase cost compared to thermal vehicles, long charging time, uncertain/undeveloped policy landscape. The scientific literature agrees with these observations, even if cost and environmental benefits appear to be the parameters with the most influence on purchase decision (Vassileva & Campillo, 2017).

Regarding charging infrastructure, the EU recommends 1 public charger for every 10 EVs, and France is yet a bit below this target, at 1 charger for 13 EVs, counting plug-in hybrids (AVERE, 2021). On the other hand, the need for charging stations seems to be conditioned by the type and density of the territory. For example, in Norway, the country with the strongest development, the infrastructure is only 1 public charger for about 30 EVs (IEA, 2021b), but there is no lack of charging stations, given the high proportion of individual housing: more than 80% of EVs are charged at home in Norway (Figenbaum & Nordbakke, 2019).

Different battery technologies are being developed, which makes it non-trivial to assess the demand for raw materials (Junne et al., 2020), but the IEA seems to indicate that a massive worldwide development is possible (IEA, 2021b). The same observation apply to the environmental impact of EV batteries that depends on the battery technology.

In the literature, the environmental benefits of EVs compared to thermal vehicles is no longer really debated in decarbonized electricity generation systems, even when calculating LCA emissions (Cihat Onat et al., 2020; Lucas et al., 2012; Ma et al., 2012; Mendoza Beltran et al., 2018; Wolfram et al., 2021). However, the ratio between BEV and thermal vehicle emissions differ according to the selected assumptions (vehicle life span, producer country, battery recycling rate, vehicle size, eco-driving, etc.). For instance, some studies indicate 4 times lower life cycle emissions for BEVs under favorable conditions at the 2050 time-horizon (Mendoza Beltran et al., 2018), while others conclude that in worst case scenarios and when accounting marginal emissions for electricity generation and large individual vehicles, BEVs generate 20% more emissions than thermal vehicles (Ma et al., 2012). Xu et al. (2020) estimates that implementing EVs reduces carbon emissions by between 36 and 47% at the European level depending on smart charging adoption. In the case of high carbon electricity generation mixes (around 400 gCO₂eq/kWh), electric propulsion is not always considered useful to mitigate climate change, even if it contributes to the reduction of local pollution in cities.

Finally, a point is raised by ADEME (2021) and IEA (2021a), relating to vehicle mass that has lately been increasing in Europe, especially via the surge of sport utility vehicles (SUVs), going against decarbonization of the transport sector. Heavier vehicles induce more consumption of resources to build and power the vehicle. Governments have introduced taxes (bonus-malus) to encourage weight reduction in vehicles, but a downward trend has not yet begun (ADEME, 2021).

Light duty vehicles are a specific vehicle type that could be classified inside "personal vehicles", that also show a great electrification potential but are not the main focus of this work.

Heavy mobility

In this section, we discuss three modes of transport grouped under the term *heavy mobility*: buses, trucks and trains. Contrary to individual vehicles, where electric propulsion (or even plug-in hybrids) seems to be the most suitable technology, several motorization and smart charging modes are emerging for this transport segment.

According to the IEA, the prospects for electrification of buses are almost as high as for light vehicles in terms of percentage of the fleet, at around 50% of electric bus sales in Europe in 2030 (IEA, 2021b). Indeed, bus trip characteristics are quite suited to electrification, with rather limited daily distances driven (150km max) at low speed, large time windows without travelling parked at the depot at night, as well as a use generally rather in urban areas, where low emission zones are potentially set up. However, there is still uncertainty about the development of battery charging technologies, between plug-in charging in the evening at the depot, or recharging during the day or during the journey, by catenaries, fast chargers at the terminal or induction charging (Bi et al., 2017). The work of this thesis will not focus on buses, but there is potential of demand flexibility for electric buses, depending on the assumptions presented here: charging location and power.

The case of trucks for freight transport is relatively different from buses, in the sense that some of them are used for very long distance trips (> 500km), so that the need for a long driving range appears to be greater than for buses. Thus, several technologies seem to be adapted to several truck segments: BEVs for local deliveries, PHEVs for medium and for longer distances, FCEVs (powered by hydrogen), EVs with catenary or in-road inductive charging or biofuels (Plötz et al., 2021; Sen et al., 2017). The charging power of electric trucks is currently experimented up to 1 MW (Mishra et al., 2022), which is 300 times larger rated power than a residential individual EV charger. In any case, given the operational constraints of trucks (need for fast charging, to be synchronized with truck loading and driver breaks), it is expected that trucks will not have as strong a potential for electric demand flexibility as light vehicles. Thus, this thesis will not focus on this segment, although the study of electric trucks demand could be relevant for some aspects related to the electrical system (especially the impact on the grid and charging infrastructure sizing, in case of very high charging power).

Finally, trains and electric tramways will be excluded from the analysis conducted in this thesis, because of their non-flexible electricity demand for the majority of the rail transport already connected to the electrical network, and which is already taken into account in the consumption forecasts, based on historical data.

Two wheelers

Motorcycles and motor scooters are a specific case in the field of transport. Indeed, their use varies widely from country to country, depending on the GDP per capita and the density of the transport network. There is a large share of two-wheelers in India and a large potential for electrification (Patil et al., 2021), for instance, but relatively little in Western European countries, less than 3% of vehicle distances travelled in France (Arafer, 2019). Although this transportation mode seems to be one of the easiest to electrify, because the technology already exists and two wheelers are not usually used for very long trips, we will not consider them in our analysis, given the low consumption expected for two wheelers in France.

The same is true for electric bikes, variants of motorcycles, in regard to their prospective energy demand, with consumption under 0.02 kWh/km, which is more than ten times lower than an electric car (Fishman & Cherry, 2016).

Micro mobilities

In recent years, new mobility modes called "micromobilities" have emerged in major European cities. Most of them can actually be classified as BEVs: electric scooters, hoverboards, single wheel scooters, etc. Although their surge has been intense in the previous years (Abduljabbar et al., 2021), especially in the largest European cities (Paris, London, Berlin), their large diffusion remain uncertain as they are mostly adapted to dense areas. Additionally, these transportation modes are very efficient per distance travelled, less than 0.05 kWh/km according to Wang et al. (2021), as compared with other individual transport modes. As a result, one should keep in mind their potential development, but they are not included in our scope of work due to their low projected electricity demand.

Other

In regards to aviation, even if the industry communicates on a strong development of hydrogen aircraft (EU Publication Office, 2020), and that Solar-Impulse demonstrators of electric aircraft have taken place, the development by 2040 of electric alternatives for the transport of passengers and goods by aircraft seems too uncertain.

For maritime transport, the electrification of ships seems to be closer than aircrafts to being techno ready, with a more extensive academic literature (Bigerna et al., 2019; Sharma & Syal, 2021; Villa et al., 2019). However, there appears to be a

strong lack of data, poorly defined public objectives for electrification of maritime transport, and the likelihood that some electric ships will be off-grid and powered mainly by solar PV panels.

Thus, airplanes and ships are outside the scope of analysis of this thesis.

1.2.3 The recent evolution of individual vehicle use in France

In France, as in many other countries (further detailed in section 2.2), the government department in charge of transport carries out a national travel survey about every ten years. There are two main outcomes of national travel surveys that are of interest for this work: the use of each means of transport by the population, and the distribution of trip data (especially distances, speeds and departure times) that help us model EV demand (as described in Chapter 3). The last two mobility data sets for France were published in 2008 and 2019 (SDES, 2008, 2019b).

First, when we compare the evolution of modal shares (which is defined as the share of *trips* made with each transport means, which differs from the share of *distances travelled*, illustrated in Figure 1.4), these studies show relatively little evolution between 2008 and 2019. Thus, the average French modal share of individual cars was reduced by 2% (from 64.8% to 62.8%), balanced by approximately a 1% rise of both public transport (to 9.1%) and walking (to 23.7%), according to SDES (2020). On its side, cycling remained stable at 2.7% of trips between 2008 and 2019. However, beyond those national averages, we observe large geographical differences in those modal share data, as individual vehicles' modal share is now reported at 33.3% in the Paris area (in a sharp downward trend), compared to 79.5% in rural areas and 73.2% in small cities, where the trend is stable.

Regarding the distribution of individual trip data inside the two most recent French national travel surveys, each study provides a list of trips, with among others information on the respondent code (anonymized), the origin and destination location (home / work / other), the type of day (week-day, Saturday or Sunday), the transport mode used, the zone of residency of the respondent (urban, rural and county), and most importantly, the departure time, arrival time and distance of the trip. The 2008 travel survey provides around 132,000 individual trips, but only 45,000 are included in the 2019 data set. In this section, we analyze and compare these studies according to the following methodology.

First, we selected trips made with a personal motorized vehicle only, and got rid of incomplete data and aberrant data (travel speeds above 150 km/h or below 5 km/h, trip length below 0.5 km). We also divided the analysis between "local mobility" and "long-distance trips", the definition provided by SDES (2008) of these categories being: if and only if a trip goes beyond 80 km away from home as the crow flies, then it is classified as a "long-distance" trip.

Second, for each respondent code, we recompiled the list of trips made through the day, in order to get the total distance driven per day, a list of departure and arrival times of each trip.

Third, we affected those daily travel data to our 3 categories: working day or week-end, urban or rural, commuting to work trip or other trip purpose.

Finally, when we compare the two most key data regarding individual trip data, between the 2008 and the 2019 study, as illustrated in Figure 1.5, we identify that there has not been a strong evolution of individual trip patterns in the last 12 years (similar distribution of daily distances driven and arrival times, considering margins of error). These national survey data are further analyzed in annex 1.A. We can try to explain this low difference between those two studies as there was little evolution in urban planning and working habits in that period in most of the territory, which means that individual trips stayed relatively similar³.

Figure 1.5 shows that the peak times of vehicle arriving back at home is the 17:00-19:00 in the evening, with a smaller peak at mid-day.

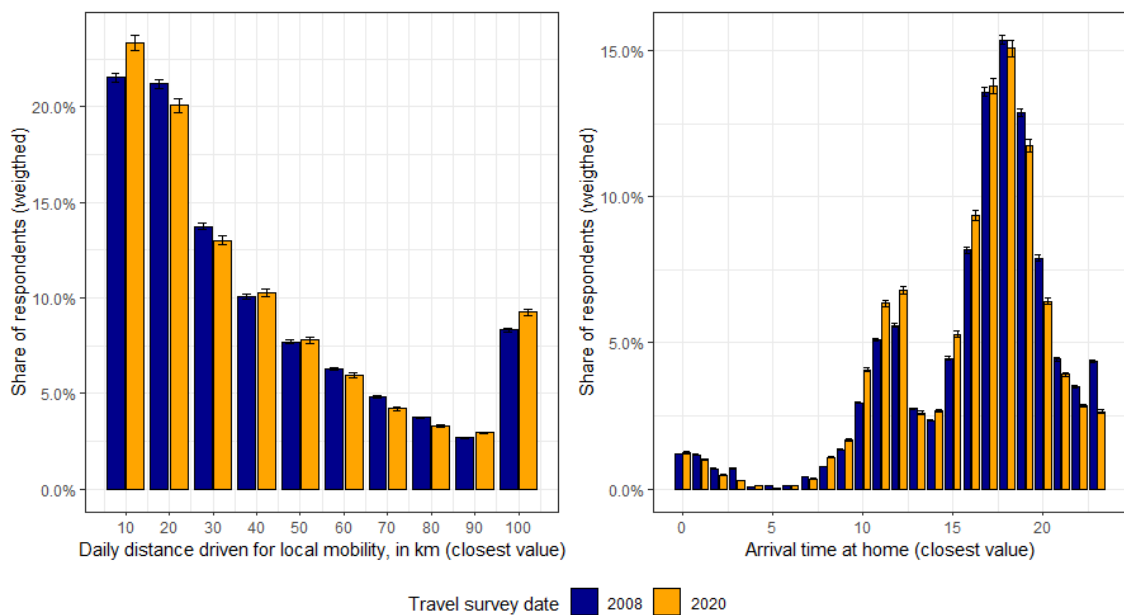


Figure 1.5: Comparison of individual trip distances and arrival time distribution for the 2008 and 2019 French national surveys

As a result of this travel data analysis, both 2008 and 2019 travel surveys can be used quite indifferently for assessing current trip patterns in individual vehicles. For the rest of this thesis, we use data from the 2008 survey to generate EV connection and demand data, which was accessible from the beginning of our work and has a larger respondent pool.

If provided detailed prospective scenario on how individual trips could evolve (e.g. decreasing the share of trips below 20km in urban areas linked to a rise of

³The previous 2019 French national travel survey was conducted just before the Covid-19 pandemic, which may induce a shift towards more home-working or other societal changes, which could modify this analysis, to be confirmed in the next few years.

public transport or decrease the share of trips for the “commuting to work” purpose in a scenario with more home-working), one could easily modify such historical travel data set in order to generate a prospective travel data set, as further detailed in section 3.2.2. However, current French national scenarios on transport evolution were found too unclear for this purpose.

1.3 A changing European power generation system

1.3.1 From a thermal electricity generation system to a decarbonized one

Similar to the transportation sector, electricity generation was massively developed during the 20th century in Western Europe, which led to an increase in energy consumption and living standards during this period. The first main resources used for electricity generation were the same as for mobility in that period (coal, gas and oil), as well as nuclear power in some countries from the 1960s/1970s onwards, notably in the USA, Western Europe, the USSR and Japan. Large hydro power plants, based on turbines in rivers with high water flow, have also been built in suitable territories (mountainous territories or territories with high water resources, such as Canada, Brazil and the Scandinavian countries). Electricity mix for the World, Europe and France in 1990 are illustrated in Figure 1.6.

Since 1990/2000, the decrease in the cost of renewable energy generation, especially solar photovoltaic (PV) and wind power, as well as environmental issues (climate, local particle pollution, and related to past nuclear accidents - Chernobyl and Fukushima) have led public authorities to push for the development of renewables as well as for private actors to invest in them. As a result, the share of renewable generation in the electricity mix reached 38% in the EU in 2020. On a global scale, electricity generation is still dominated by fossil fuels, notably coal (36%) and gas (23%) (Ritchie et al., 2022).

Moreover, the international ambitions to further decarbonize the electricity generation sector lead to the elaboration of scenarios as presented in Figure 1.6, with around two thirds of renewable generation by 2050. The potential for development of hydro generation is identified as rather limited compared to other renewable sources, as a result, the share of hydro-generated electricity is expected to decrease (both worldwide, in EU and in France), due to the increasing projected electricity demand. In addition, many research studies now indicate the possibility of reaching 100% renewable electricity mixes by 2050, which would further reduce the flexibility provided by electricity generation (Bussar et al., 2016; RTE, 2021; Zappa et al., 2019). The data sources in the following graph are only selected for illustration purposes and are not used as base case scenarios in the following of this work.

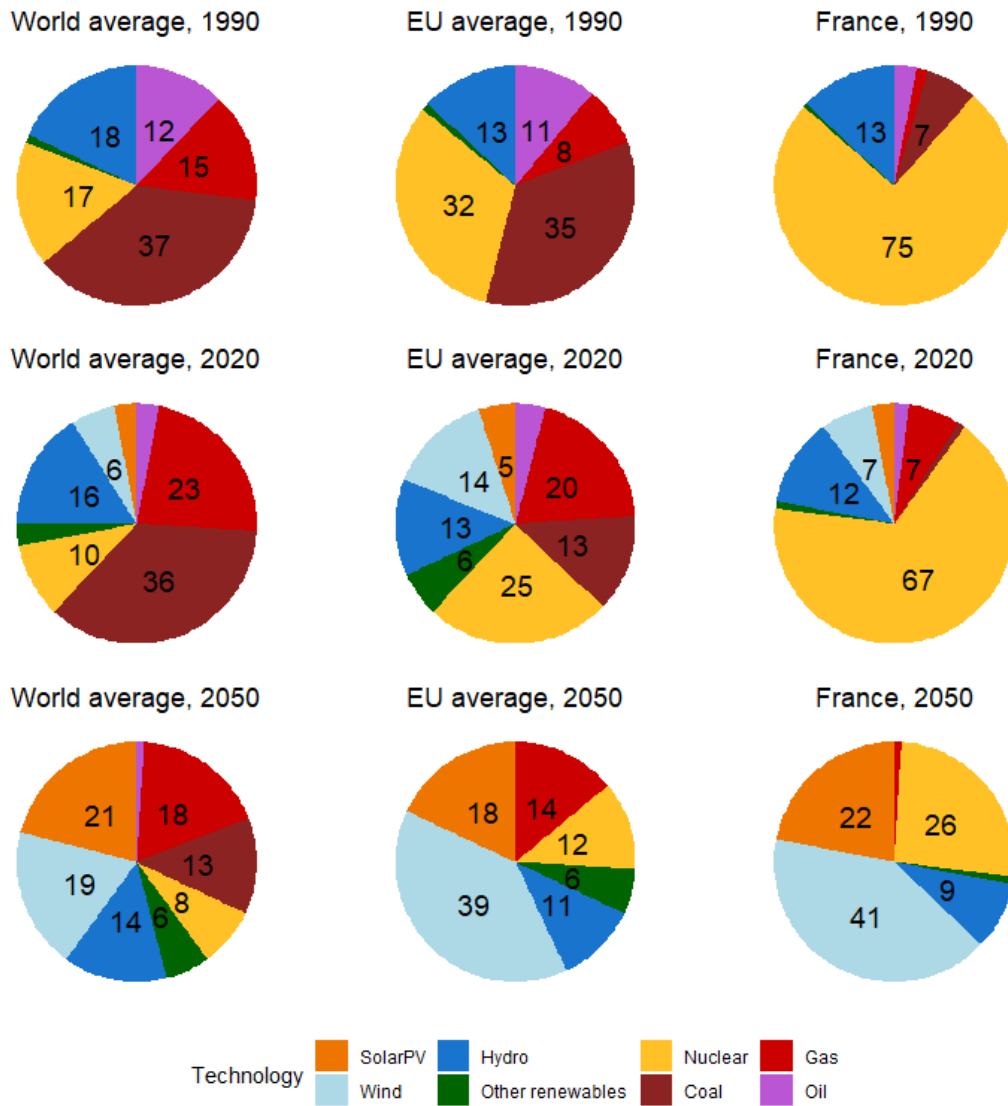


Figure 1.6: Electricity generation mix evolution (share of generated electricity) at three different scales: World, EU and France. Data for 1990 and 2020 from Ritchie et al. (2022), data for World average in 2050 from the Stated Policies scenario of IEA (2021c), data for EU average in 2050 from the EU reference scenario of European Commission (2020) and data for France in 2050 from the N1 scenario of RTE (2021)

1.3.2 The development of demand-side flexibility

Heggarty et al. (2020) defines flexibility and assesses who provides flexibility in France on three different scales: daily, weekly and annual. Thermal sources account for a large share of the flexibility provided to current power systems.

As described in the previous section, a significant share of thermal sources are expected to be replaced by renewable sources over the next 30 years, which implies that new solutions need to be developed to compensate this loss of flexibil-

ity. Among these solutions, most prospective electricity scenarios (IEA, 2021c; RTE, 2021) advise a growth of interconnectors between electric zones, the development of stationary storage (hydro, batteries, compressed air, etc.), sector coupling (especially with gas and hydrogen) and finally a rise in demand-side flexibility, which is the focus of this section, and more broadly this thesis.

When studying the literature on the topic of demand-side flexibility (or demand response), it appears that several main sectors seem to be well suited: the industrial sector, the residential sector, the commercial sector (Golmohamadi, 2022; Heffron et al., 2020; Kohlhepp et al., 2019; Li & Pye, 2018; Söder et al., 2018), as well as the transportation sector (sometimes included in the residential sector for electric cars). It is to be noted that demand-side flexibility is already slightly developed in France in 2021, especially through industrial load management and time-of-use tariffs for the residential sector (from late 20th century in France).

Multiple residential appliances have a potential for flexibility (heating, domestic hot water, dishwashers, washing machines, charging of small battery-powered electronic devices), but on the prospective horizon, EVs which present a significant part of the potential for demand flexibility can be easily mobilized, along with hydrogen electrolyzers (National Grid, 2021; RTE, 2021).

Additionally, it appears that EV load flexibility is more suited to providing short term (especially daily) than annual flexibility (Heggarty et al., 2020), as opposed to H₂ electrolyzers. Helistö et al. (2018) also indicates, by comparing the benefits of demand-side flexibilities, that EVs are most useful on a daily basis, to facilitate the integration of solar generation. Other studies support this PV-EV complementarity (Hoarau & Perez, 2018; Schuller et al., 2015).

In order to manage demand-side flexibility, for the case of EVs, several smart charging modes are developed: tariff-based control modes (already developed for the other main flexible uses) can be used, as well as other dynamic modes, based on real-time communication, either unidirectional or bidirectional (vehicle-to-grid), which will be presented in more detail in Chapter 4, focused on EV smart charging.

Another simpler lever to limit residential peak consumption is to allocate a share of capacity-based tariffs instead of 100% energy based tariffs, which facilitates EV integration for power systems (Freitas Gomes et al., 2021).

In the following section, the main areas of interaction between EV flexibility and power systems will be detailed.

1.4 The interaction between transport and electricity systems

After identifying the potential for EV demand *flexibility*, five main areas of study for this flexibility are identified (Golmohamadi, 2022; Thompson & Perez, 2019):

- **Generation capacity and transport network expansion:** the challenge is to size the power system at the right level (minimize cost and keep sufficient

quality of supply), while taking into account consumption and its flexibility in the future. The integration of flexible consumption trajectories in these models is the most macro subject of study for EV demand.

- **Optimal dispatch:** charging EVs at the least costly time windows (minimizing the use of carbon-based generation), for a given power system. This is the main focus of this thesis, presented in Chapter 4. Another approach to deal with this aspect is from a "valley-filling" point of view to limit the electrical system sizing.
- **Network flows,** at the distribution and transmission level: manage or prevent grid congestion, in order to minimize overloads on the network lines and transformers. Voltage support is a related topic to network studies.
- **Intraday markets:** study the offers that can be proposed by the aggregation of vehicles on the day-ahead and intraday markets. The purpose of this subject is mainly to adapt the production and consumption plans a few hours ahead of real time to compensate for weather forecasting, unforeseen events, etc.
- **Frequency regulation,** either frequency containment reserve (FCR) or automatic frequency restoration reserve (aFRR): keeping enough flexibility assets connected to manage the frequency in real time.

The compatibility of the different EV smart charging modes (time-of-use, unidirectional smart charging and V2G) with these power system issues are further detailed in section 2.3.1, and the main models and methods used to address them in section 4.2.1.

After the identification of these five interaction topics, it should be noted that the relevant time horizons of study differ between these topics. Indeed, some of them (frequency regulation, network flows on specific locations) are relevant as soon as the EVs are lightly developed. Others, such as network impact on the majority of areas and optimal dispatch, are more long-term research questions, when EVs become predominant on the vehicle market. This thesis, whose mobility analysis will be made on the French case, aims to study the 2040 time horizon, a few years after the planned end of sales of thermal vehicles.

1.5 Scope of work and research questions

As identified in this Chapter, our work studies the demand side flexibility of electric vehicles, at the intersection of the electricity and transport sectors, with a focus on the 2040 time-horizon, an important milestone of transport electrification. The scope of this thesis is mainly the electrification of light vehicles in France and its interaction with the European electrical system dispatch.

We try to complement the existing literature on the topic (further detailed in Chapter 2) by providing a methodology to integrate EV demand data (computed

from a mobility model and a travel survey dataset) inside a modeling of the European electricity system. This analysis enables the study of the impact of various EV charging scenarios on the electricity generation costs and carbon emissions. The competition between EV demand flexibility and other flexibility means (stationary batteries, industrial load management, pumped hydro storage, hydrogen, etc.) is also taken into account in this modeling framework. Additionally, the influence of electricity-generation scenarios (such as gas prices) on EV flexibility value can be studied.

The research objectives of this thesis can be summarized in these research questions :

How to model the prospective integration into the power system of a large EV diffusion at the national scale?

How to compare the main EV smart charging modes, and which parameters have the largest impacts on this demand-side flexibility potential?

1.6 Thesis structure

Following this introductory Chapter, in order to address these two research questions, we adopt a 3-Chapter structure, with the results and methods of each Chapter directly feeding into the next, as illustrated in Figure 1.7.

Chapter 2 presents the literature review conducted on the topic of vehicle trips modeling, for different research objectives related to EV integration into the electric system. It appears that several classes of models emerge, each adapted to a specific research question. Secondly, the objective functions related to the EV smart charging (either to limit the local power demand, to minimize the charging cost or to maximize the self-consumed energy share) are described. Most of the studies focus on a precise modeling of either the electrical system or the transportation sector. This approach is justified in the short term, given the current limited market share of EVs. On the other hand, for prospective studies, we recommend sequential modeling the transportation system and then the electric system. Finally, this Chapter ends with recommendations for modeling approaches for the research topics identified by the literature review, and in particular for the topic that will be addressed in the rest of this thesis.

Chapter 3 describes the method used to generate EV uncontrolled demand and connection data at the national level from a transportation survey dataset, building on the observations in the previous Chapter. We also identify points where these datasets are not sufficient to ensure accurate modeling (the very local aspect as well as long-distance trips). The solutions to adapt these tools in order to study the connection of several types of vehicles, for various time horizons and charging infrastructures are also detailed. In a second step, our methodology is applied to a case study on EV demand in France by 2040, for an ambitious EV development scenario. We identify the parameters that have the most influence on EV demand data (energy needed and connection to the grid patterns), and pave

the way to the study of the smart charging of these EVs, thanks to the multitude of output data generated.

Chapter 4 completes the methodology of this thesis by integrating the previous results into a simulation model of the electrical system with the optimal dispatch point of view (while modeling the exchanges between European countries), which enables the study and comparison of all the smart charging modes that are currently being developed (uncontrolled charge, time-of-use tariffs, dynamic smart charging and V2H/V2G). We also show how to aggregate millions of EVs into a single modeling object, with associated limitations and proposals to overcome them. Finally, a case study following the results provided in Chapter 3 allows us to draw some first conclusions on the comparison of these smart charging modes, with respect to the challenges of the electric system in 2040 that these modes will be able to answer. The identification of the main parameters that influence the flexibility of EVs is also performed. Finally, we conclude by indicating the main barriers to be removed to develop the demand-side flexibility provided by electric vehicles, while having proven and enabled our ability to measure the associated economic and environmental gains.

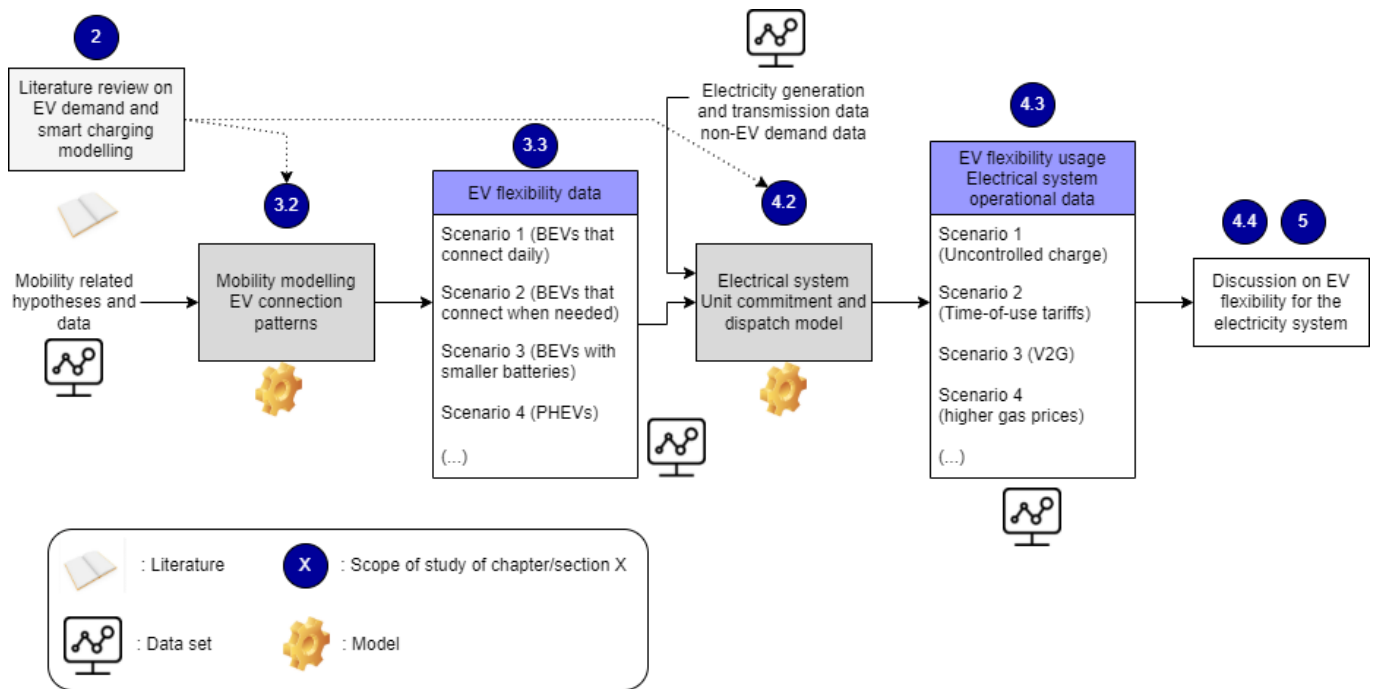


Figure 1.7: Global framework of our methodology to study EV grid integration

Bibliography

- Abduljabbar, R. L., Liyanage, S., & Dia, H. (2021). The role of micro-mobility in shaping sustainable cities: A systematic literature review. *Transportation research part D: transport and environment*, 92, 102734. <https://doi.org/https://doi.org/10.1016/j.trd.2021.102734>
- Abu-Allaban, M., Gillies, J. A., Gertler, A. W., Clayton, R., & Proffitt, D. (2003). Tailpipe, resuspended road dust, and brake-wear emission factors from on-road vehicles. *Atmospheric environment*, 37(37), 5283–5293. <https://doi.org/https://doi.org/10.1016/j.atmosenv.2003.05.005>
- ADEME. (2021). Évolution du marché, caractéristiques environnementales et techniques. véhicules particuliers neufs vendus en france. <https://librairie.ademe.fr/mobilite-et-transport/771-plus-de-vehicules-electriques-trop-de-suv.html>
- Arafer. (2019). Bilan de la circulation, dgac, enquête annuelle sur les transports collectifs urbains (cerema, cgdd, dgitm, gart, utp), ensemble des opérateurs ferroviaires, île-de-france mobilités-omnil, utp. <https://www.notre-environnement.gouv.fr/rapport-sur-l-etat-de-l-environnement/themes-ree/enjeux-de-societe/modes-de-vie-des-menages/mobilite/article/evolution-du-mode-de-deplacements-des-menages>
- AVERE. (2021). Baromètres de la recharge - 49 914 points de recharge ouverts au public en france au 31 octobre 2021.
- Bi, Z., De Kleine, R., & Keoleian, G. A. (2017). Integrated life cycle assessment and life cycle cost model for comparing plug-in versus wireless charging for an electric bus system. *Journal of Industrial Ecology*, 21(2), 344–355. <https://doi.org/https://doi.org/10.1111/jiec.12419>
- Bigerna, S., Micheli, S., & Polinori, P. (2019). Willingness to pay for electric boats in a protected area in italy: A sustainable tourism perspective. *Journal of Cleaner Production*, 224, 603–613. <https://doi.org/https://doi.org/10.1016/j.jclepro.2019.03.266>
- Bigo, A. (2020). Les transports face au défi de la transition énergétique. Explorations entre passé et avenir, technologie et sobriété, accélération et ralentissement. *PhD dissertation*, 341. <https://tel.archives-ouvertes.fr/tel-03082127>
- Bugliarello, G., Alexandre, A., & Barnes, J. (2014). *The impact of noise pollution: A socio-technological introduction*. Elsevier.
- Burton, N. (2013). *History of electric cars*. Crowood.
- Bussar, C., Stöcker, P., Cai, Z., Moraes Jr., L., Magnor, D., Wiernes, P., van Bracht, N., Moser, A., & Sauer, D. U. (2016). Large-scale integration of renewable energies and impact on storage demand in a european renewable power system of 2050—sensitivity study. *Journal of Energy Storage*, 6, 1–10. <https://doi.org/https://doi.org/10.1016/j.est.2016.02.004>

- Cai, J. (2022). The development of new energy industry under the implementation of china's environmental protection policy—the forecast of lithium ion and sodium ion battery industry. *2022 7th International Conference on Financial Innovation and Economic Development (ICFIED 2022)*, 1616–1619. <https://doi.org/10.1088/1742-6596/1347/1/012087>
- César, A., Carvalho Jr, J., & Nascimento, L. (2015). Association between nox exposure and deaths caused by respiratory diseases in a medium-sized brazilian city. *Brazilian Journal of Medical and Biological Research*, *48*, 1130–1135. <https://doi.org/10.1590/1414-431X20154396>
- Cihat Onat, N., Aboushaqrah, N. N., Kucukvar, M., Tarlochan, F., & Magid Hamouda, A. (2020). From sustainability assessment to sustainability management for policy development: The case for electric vehicles. *Energy Conversion and Management*, *216*, 112937. <https://doi.org/10.1016/j.enconman.2020.112937>
- Citepa. (2022). Inventaire des émissions de polluants atmosphériques et de gaz à effet de serre en France Format Secten. https://www.citepa.org/wp-content/uploads/Citepa_Rapport-Secten-2022_Transports_v1.1.pdf
- Conway, G., Joshi, A., Leach, F., García, A., & Senecal, P. K. (2021). A review of current and future powertrain technologies and trends in 2020. *Transportation Engineering*, *5*, 100080. <https://doi.org/10.1016/j.treng.2021.100080>
- Costa, L., Moreau, V., Thurm, B., Yu, W., Clora, F., Baudry, G., Warmuth, H., Hezel, B., Seydewitz, T., Ranković, A., Kelly, G., & Kropp, J. P. (2021). The decarbonisation of Europe powered by lifestyle changes. *Environmental Research Letters*, *16*(4), 044057. <https://doi.org/10.1088/1748-9326/abe890>
- EU Publication Office. (2020). Hydrogen-powered aviation : A fact-based study of hydrogen technology, economics, and climate impact by 2050, fuel cells and hydrogen 2 joint undertaking. <https://data.europa.eu/doi/10.2843/471510>
- European Commission. (2020). Eu reference scenario 2020, last accessed online in june 2022. https://energy.ec.europa.eu/data-and-analysis/energy-modelling/eu-reference-scenario-2020_en
- Figenbaum, E., & Nordbakke, S. (2019). Battery electric vehicle user experiences in norway's maturing market. <https://trid.trb.org/view/1659499>
- Fishman, E., & Cherry, C. (2016). E-bikes in the mainstream: Reviewing a decade of research. *Transport Reviews*, *36*(1), 72–91. <https://doi.org/10.1080/01441647.2015.1069907>
- Freitas Gomes, I. S., Perez, Y., & Suomalainen, E. (2021). Rate design with distributed energy resources and electric vehicles: A californian case study. *Energy Economics*, *102*, 105501. <https://doi.org/10.1016/j.eneco.2021.105501>
- Goldie-Scot, L., & BloombergNEF. (2019). A behind the scenes take on lithium-ion battery prices. <https://about.bnef.com/blog/behind-scenes-take-lithium-ion-battery-prices/>

- Golmohamadi, H. (2022). Demand-Side Flexibility in Power Systems: A Survey of Residential, Industrial, Commercial, and Agricultural Sectors. *Sustainability*, 14(13), 7916. <https://doi.org/10.3390/su14137916>
- Haasz, T., Gómez Vilchez, J. J., Kunze, R., Deane, P., Fraboulet, D., Fahl, U., & Mulholland, E. (2018). Perspectives on decarbonizing the transport sector in the EU-28. *Energy Strategy Reviews*, 20, 124–132. <https://doi.org/10.1016/j.esr.2017.12.007>
- Heffron, R., Körner, M.-F., Wagner, J., Weibelzahl, M., & Fridgen, G. (2020). Industrial demand-side flexibility: A key element of a just energy transition and industrial development. *Applied Energy*, 269, 115026. <https://doi.org/https://doi.org/10.1016/j.apenergy.2020.115026>
- Heggarty, T., Bourmaud, J.-Y., Girard, R., & Kariniotakis, G. (2020). Quantifying power system flexibility provision. *Applied Energy*, 279, 115852. <https://doi.org/10.1016/j.apenergy.2020.115852>
- Helistö, N., Kiviluoma, J., & Holttinen, H. (2018). Long-term impact of variable generation and demand side flexibility on thermal power generation. *IET Renewable Power Generation*, 12(6), 718–726. <https://doi.org/10.1049/iet-rpg.2017.0107>
- Hoarau, Q., & Perez, Y. (2018). Interactions between electric mobility and photovoltaic generation: A review. *Renewable and Sustainable Energy Reviews*, 94, 510–522. <https://doi.org/10.1016/j.rser.2018.06.039>
- IEA. (2019). *Global EV Outlook 2019: Scaling-up the transition to electric mobility*. OECD. <https://doi.org/10.1787/35fb60bd-en>
- IEA. (2021a). Fuel consumption of cars and vans. <https://www.iea.org/reports/fuel-consumption-of-cars-and-vans>
- IEA. (2021b). Global EV Outlook 2021. <https://www.iea.org/reports/global-ev-outlook-2021>
- IEA. (2021c). World energy outlook 2018, 661.
- INSEE. (2017). Tableaux de l'économie française, budget des ménages, 1. <https://www.insee.fr/fr/statistiques/4764315>
- INSEE. (2020). Tableaux de l'économie française, équipements des ménages. <https://www.insee.fr/fr/statistiques/4277714?sommaire=4318291#documentation>
- IPCC. (1992). *Climate change: The 1990 and 1992 IPCC assessments, IPCC first assessment report overview and policymaker summaries and 1992 IPCC supplement* (IPCC & WMO, Eds.).
- IPCC. (2022). Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. <https://www.ipcc.ch/report/ar6/wg2/>
- Junne, T., Wulff, N., Breyer, C., & Naegler, T. (2020). Critical materials in global low-carbon energy scenarios: The case for neodymium, dysprosium, lithium, and cobalt. *Energy*, 211, 118532. <https://doi.org/https://doi.org/10.1016/j.energy.2020.118532>

- Kaya, Y. (1990). Impact of carbon dioxide emission control on gnp growth : Interpretation of proposed scenarios. *IPCC Energy and Industry Subgroup, Response Strategies Working Group*.
- Kohlhepp, P., Harb, H., Wolisz, H., Waczowicz, S., Müller, D., & Hagenmeyer, V. (2019). Large-scale grid integration of residential thermal energy storages as demand-side flexibility resource: A review of international field studies. *Renewable and Sustainable Energy Reviews*, *101*, 527–547. <https://doi.org/10.1016/j.rser.2018.09.045>
- Le Quéré, C., Jackson, R. B., Jones, M. W., Smith, A. J. P., Abernethy, S., Andrew, R. M., De-Gol, A. J., Willis, D. R., Shan, Y., Canadell, J. G., Friedlingstein, P., Creutzig, F., & Peters, G. P. (2020). Temporary reduction in daily global CO₂ emissions during the COVID-19 forced confinement. *Nature Climate Change*, *10*(7), 647–653. <https://doi.org/10.1038/s41558-020-0797-x>
- Li, P.-H., & Pye, S. (2018). Assessing the benefits of demand-side flexibility in residential and transport sectors from an integrated energy systems perspective. *Applied Energy*, *228*, 965–979. <https://doi.org/10.1016/j.apenergy.2018.06.153>
- Lucas, A., Alexandra Silva, C., & Costa Neto, R. (2012). Life cycle analysis of energy supply infrastructure for conventional and electric vehicles. *Energy Policy*, *41*, 537–547. <https://doi.org/10.1016/j.enpol.2011.11.015>
- Ma, H., Balthasar, F., Tait, N., Riera-Palou, X., & Harrison, A. (2012). A new comparison between the life cycle greenhouse gas emissions of battery electric vehicles and internal combustion vehicles. *Energy Policy*, *44*, 160–173. <https://doi.org/10.1016/j.enpol.2012.01.034>
- Matthews, H. S., Hendrickson, C. T., & Weber, C. L. (2008). The importance of carbon footprint estimation boundaries [PMID: 18767634]. *Environmental Science & Technology*, *42*(16), 5839–5842. <https://doi.org/10.1021/es703112w>
- Mendoza Beltran, A., Cox, B., Mutel, C., Vuuren, D. P., Font Vivanco, D., Deetman, S., Edelenbosch, O. Y., Guinée, J., & Tukker, A. (2018). When the Background Matters: Using Scenarios from Integrated Assessment Models in Prospective Life Cycle Assessment. *Journal of Industrial Ecology*. <https://doi.org/10.1111/jiec.12825>
- Merger, M. (1987). Transport history in france: A bibliographical review. *The Journal of Transport History*, *8*(2), 179–201. <https://doi.org/10.1177/002252668700800205>
- Mishra, P., Miller, E., Santhanagopalan, S., Bennion, K., & Meintz, A. (2022). A framework to analyze the requirements of a multiport megawatt-level charging station for heavy-duty electric vehicles. *Energies*, *15*(10). <https://doi.org/10.3390/en15103788>
- National Grid. (2021). Future energy scenarios.
- NOAA, N. (2022). Climate at a glance: Global time series, last accessed june 2022 from. <https://www.ncei.noaa.gov/cag/>
- Oroumiyeh, F., & Zhu, Y. (2021). Brake and tire particles measured from on-road vehicles: Effects of vehicle mass and braking intensity. *Atmospheric Environment: X*, *12*, 100121. <https://doi.org/10.1016/j.aeaoa.2021.100121>

- Paredes, M., Pomilio, J. A., & Santos, A. A. (2013). Combined regenerative and mechanical braking in electric vehicle. *2013 Brazilian Power Electronics Conference*, 935–941. <https://doi.org/10.1109/COBEP.2013.6785227>
- Patil, M., Majumdar, B. B., Sahu, P. K., & Truong, L. T. (2021). Evaluation of prospective users' choice decision toward electric two-wheelers using a stated preference survey: An indian perspective. *Sustainability*, *13*(6), 3035. <https://doi.org/https://doi.org/10.3390/su13063035>
- Plötz, P., Wachsmuth, J., Gnann, T., Neuner, F., Speth, D., & Link, S. (2021). Net-zero-carbon transport in europe until 2050.
- Ritchie, H., Roser, M., & Rosado, P. (2020). CO₂ and greenhouse gas emissions. *Our World in Data*. <https://ourworldindata.org/co2-and-other-greenhouse-gas-emissions>
- Ritchie, H., Roser, M., & Rosado, P. (2022). Energy, electricity mix. <https://ourworldindata.org/electricity-mix>
- Rottoli, M., Dirnaichner, A., Pietzcker, R., Schreyer, F., & Luderer, G. (2021). Alternative electrification pathways for light-duty vehicles in the european transport sector. *Transportation Research Part D: Transport and Environment*, *99*, 103005. <https://doi.org/https://doi.org/10.1016/j.trd.2021.103005>
- RTE. (2019). Integration of electric vehicles into the power system in France.
- RTE. (2021). Energy pathways to 2050.
- Schuller, A., Flath, C. M., & Gottwalt, S. (2015). Quantifying load flexibility of electric vehicles for renewable energy integration. *Applied Energy*, *151*, 335–344. <https://doi.org/10.1016/j.apenergy.2015.04.004>
- SDES. (2008). Enquête nationale transports et déplacements (entd) 2008. <https://www.statistiques.developpement-durable.gouv.fr/enquete-nationale-transports-et-deplacements-entd-2008>
- SDES. (2019a). Bilan énergétique de la France pour 2019.
- SDES. (2019b). Enquête sur la mobilité des personnes 2018-2019. <https://www.statistiques.developpement-durable.gouv.fr/enquete-sur-la-mobilite-des-personnes-2018-2019>
- SDES. (2020). Comment les français se déplacent-ils en 2019 ? résultats de l'enquête mobilité des personnes.
- SDES. (2021). Chiffres clés du climat, France, Europe et Monde. <https://www.statistiques.developpement-durable.gouv.fr/edition-numerique/chiffres-cles-du-climat/>
- Sen, B., Ercan, T., & Tatari, O. (2017). Does a battery-electric truck make a difference? – life cycle emissions, costs, and externality analysis of alternative fuel-powered class 8 heavy-duty trucks in the united states. *Journal of Cleaner Production*, *141*, 110–121. <https://doi.org/https://doi.org/10.1016/j.jclepro.2016.09.046>
- Sharma, K., & Syal, P. (2021). A review on solar powered boat design. *International Research Journal on Advanced Science Hub*, *3*(Special Issue 9S), 1–10. <https://doi.org/10.47392/irjash.2021.241>

- SNBC, D. (2019). Synthèse du scénario de référence de la stratégie française pour l'énergie et le climat - SNBC, 47.
- Söder, L., Lund, P. D., Koduvere, H., Bolkesjø, T. F., Rossebø, G. H., Rosenlund-Soysal, E., Skytte, K., Katz, J., & Blumberga, D. (2018). A review of demand side flexibility potential in Northern Europe. *Renewable and Sustainable Energy Reviews*, 91, 654–664. <https://doi.org/10.1016/j.rser.2018.03.104>
- Thompson, A. W., & Perez, Y. (2019). Vehicle-to-Everything (V2X) energy services, value streams, and regulatory policy implications. *Energy Policy*, 111136. <https://doi.org/10.1016/j.enpol.2019.111136>
- Vassileva, I., & Campillo, J. (2017). Adoption barriers for electric vehicles: Experiences from early adopters in Sweden. *Energy*, 120, 632–641. <https://doi.org/10.1016/j.energy.2016.11.119>
- Villa, D., Montoya, A., & Ciro, J. M. (2019). The electric boat charging problem. *Production*, 29. <https://doi.org/10.1590/0103-6513.20190067>
- Wang, Y., Wu, J., Chen, K., & Liu, P. (2021). Are shared electric scooters energy efficient? *Communications in Transportation Research*, 1, 100022. <https://doi.org/https://doi.org/10.1016/j.commtr.2021.100022>
- Wolfram, P., Tu, Q., Heeren, N., Pauliuk, S., & Hertwich, E. G. (2021). Material efficiency and climate change mitigation of passenger vehicles. *Journal of Industrial Ecology*, 25(2), 494–510. <https://doi.org/https://doi.org/10.1111/jiec.13067>
- Xu, L., Yilmaz, H. Ü., Wang, Z., Poganietz, W.-R., & Jochem, P. (2020). Greenhouse gas emissions of electric vehicles in Europe considering different charging strategies. *Transportation Research Part D: Transport and Environment*, 87, 102534. <https://doi.org/https://doi.org/10.1016/j.trd.2020.102534>
- Zappa, W., Junginger, M., & van den Broek, M. (2019). Is a 100% renewable European power system feasible by 2050? *Applied Energy*, 233-234, 1027–1050. <https://doi.org/10.1016/j.apenergy.2018.08.109>

1.A Additional travel survey analysis results

To complement the analysis made in section 1.2.3, similar data on the analysis of three trip categories are illustrated here.

First, Figures 1.8 and 1.9 show the discrepancy between the mobility habits of urban and rural dwellers. Even if, as for average national data, the differences between the two data sets is really small (nearly always inside the 95% confidence interval), it appears that rural dwellers drive significantly longer distances, and get back at home slightly earlier than in urban areas.

Then, Figure 1.10 highlight how much mobility behaviors differ in the weekends, with obviously much less people commute to work on these days, which means that fewer French people finish their last trip of the day at peak return time (17:00-19:00), with more arrival times earlier (11:00-13:00) and later (22:00-02:00) than on week days. Additionally, distances driven on weekends are very similar to those driven on week days (Figure 1.5), although less French people use their car on weekends for local mobility trips.

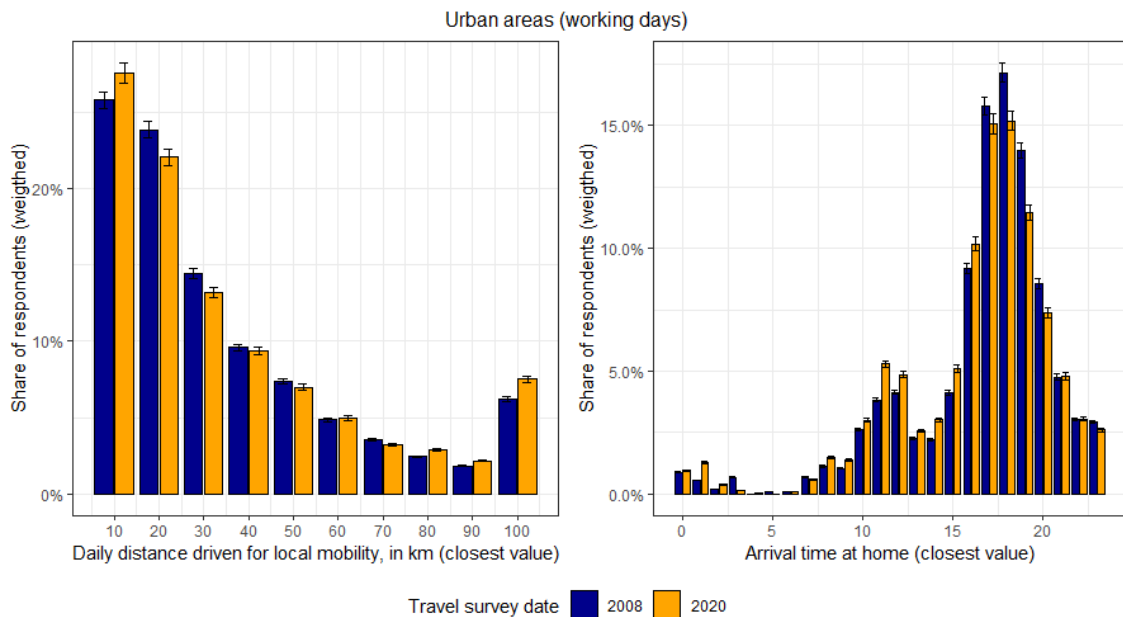


Figure 1.8: Comparison of individual trip distances and arrival time distribution for the 2008 and 2019 French national surveys (filtered, only trips on working days, in urban areas are illustrated)

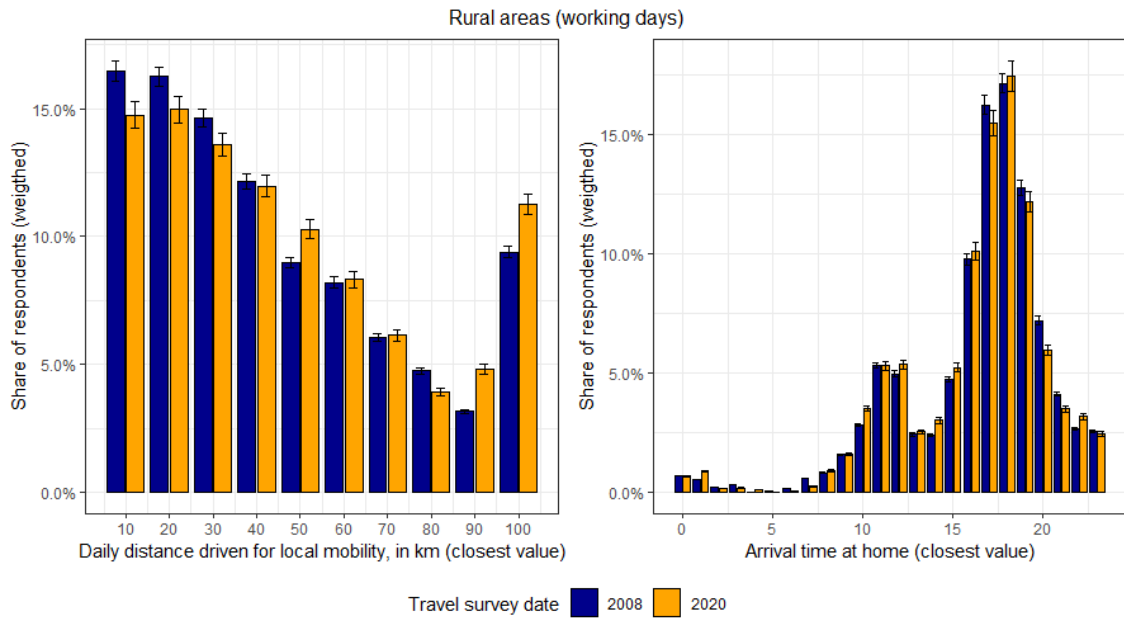


Figure 1.9: Comparison of individual trip distances and arrival time distribution for the 2008 and 2019 French national surveys (filtered, only trips on working days, in rural areas are illustrated)

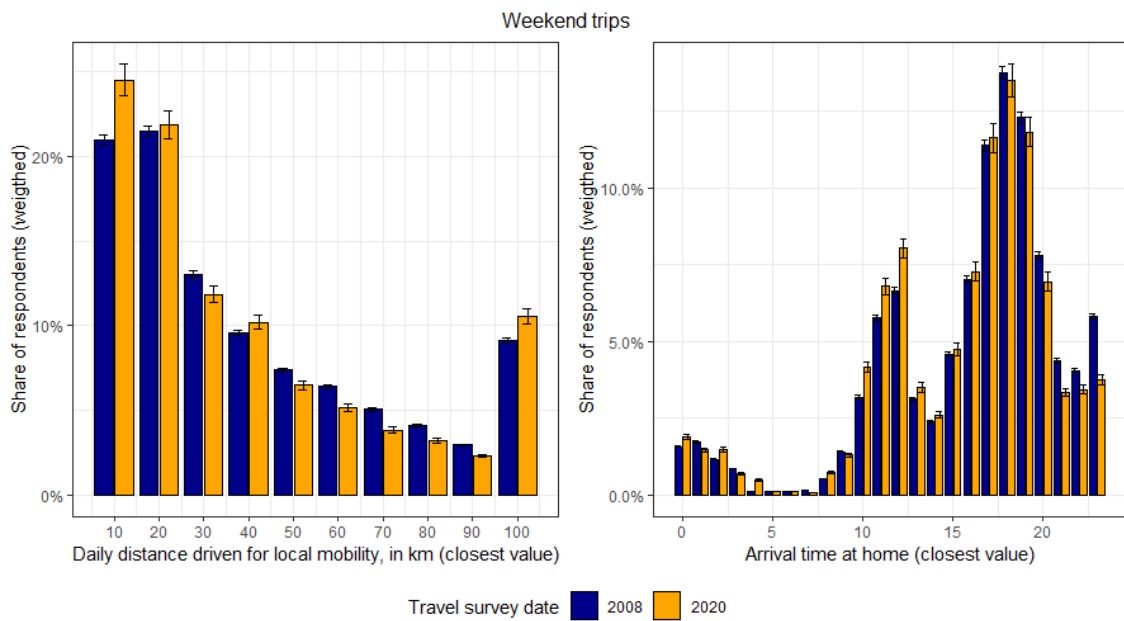


Figure 1.10: Comparison of individual trip distances and arrival time distribution for the 2008 and 2019 French national surveys (filtered, only trips on week-ends are illustrated)

2 - Chapter 2: Review of electric vehicle uncontrolled demand and smart charging modeling

Summary

Electric vehicles (EVs) offer an opportunity to move towards greenhouse gas emission reduction targets by decarbonizing the transport sector, while also reducing local air pollution. However, uncontrolled and simultaneous charging of a significant number of EVs could pose a challenge to power grids and generation-load adequacy. Studying these impacts requires a predictive model of EV fleet recharging. Here we review techniques for EV charging pattern modeling and the types of studies they are used for. This Chapter also introduces the wide range of parameters (vehicle types, charging points, plug-in behavior, etc.) that modeling studies can factor in, and the EV smart charging simulation approaches available. We conclude by proposing a framework for future research on EV load prediction models.

2.1 Introduction

Electric mobility with low-carbon electricity generation is one of the most promising solutions for reducing (on the carbon intensity of energy lever) local air pollution (especially nitrogen oxides) and the carbon footprint of transport, which accounted for a quarter of the world's total carbon emissions in 2017. Passenger cars and light-duty vehicles, which are the main focus of this thesis, are responsible for more than half of total transport carbon emissions (IEA, 2021). Governments around the world are incentivizing the adoption of electric mobility to help meet greenhouse gas emission reduction targets. Therefore, more and more drivers consider switching from an internal combustion engine vehicle (ICEV) to an electric vehicle (EV), either a plug-in hybrid EV (PHEV) or fully electric battery EV (BEV). As a result, the share of EVs in fleets is widely expected to grow over the coming decades.

EV batteries are currently mostly recharged at charging points by connecting the vehicle to a power system (the power grid, a generating system, or another storage system) when the vehicle is parked. Dynamic wireless charging is also being developed, but this technology is not predicted to be a significant share of installed chargers in the short to mid term, as this technology appears to be more costly and less energy efficient than traditional charging stations (IEA, 2019). A major field of the scientific literature on EVs hence concerns the interactions between their charging behavior and the power system, both in terms of its operation and investment planning.

The development of electric mobility could pose challenges to power systems if most EV charging is uncontrolled at electricity peak demand. Increasing peak load may require investments in power networks to strengthen the grid and in gener-

ation sources to match peak demand. However, EVs also provide an opportunity to bring flexibility to power systems through smart-charging, vehicle-to-grid (V2G) and similar technologies (see the seminal work of Kempton and Tomić, 2005). This additional flexibility can support the adequacy of power networks as they integrate an increasing share of intermittent renewable energy sources (mainly wind farms and photovoltaic panels) into electricity generation systems (Richardson, 2013).

To address interactions between different phenomena, many models have been created to simulate the connections of electric vehicles to the grid to obtain the resulting load curve for a given fleet of vehicles. This multiplication of approaches can simultaneously bring confusion and complexity if a proper roadmap is not provided. This Chapter aims to identify which load modeling approach is best suited for the studies needed by transmission system operators (TSO), distribution system operators (DSO) and other industrial actors on the impacts of EVs on their current and future power network.

The Chapter is structured as follow: First, we describe which data is commonly used for simulating EV user charging behavior and to what extent the diversity of a fleet's vehicles is taken into account (battery capacity, consumption, etc.), the multiple plugging and charging behaviors of EV owners, and the range of power and charging station locations available. Second, we introduce a wide range of EV charging models along with the type of studies they have been designed for. After highlighting the strengths and weaknesses of each model, we analyze which are the relevant modeling aspects to incorporate in case studies on EVs and which gaps in the literature need to be addressed to do this efficiently. Finally, we discuss the various methods for generating smart charging (unidirectional or with V2G) load curves, based on mobility needs.

2.2 Mobility data and model approaches for BEV

Battery electric vehicles (BEVs) are currently developing at a high pace in several areas of the world including China, Japan, the USA, Northern Europe and Western Europe (IEA, 2021), which have focused most of the published research on electric mobility and its impact on power networks. Most of these countries have an organization, often funded by the government, which surveys the patterns of car usage and other means of transport every few years. Examples include the US National Household Travel Survey (U.S. Department of Transportation, 2017), the UK National Travel Survey (UK Statistics Authority, 2018) and the French Enquête Nationale transports et déplacements (SDES, 2008)¹. In addition, city councils sometimes conduct their own local surveys in order to advise urban planning policy (Bowman & Ben-Akiva, 2001; Galus et al., 2012; Mehta et al., 2018; Shahidinejad et al., 2012).

¹A more recent mobility study has been carried out in France in 2018/2019 (SDES, 2019), but as stated in Chapter 1, this work will use the 2008 French national travel survey

Pasaoglu et al. (2013) tackled fairly specific data usage to compare EV load curve projections based on travel data for Italy, Poland, France, Germany, Spain and the UK in a study commissioned by the European Commission Joint Research Center that stratifies data by country and by day of the week. The result highlights differences between zones and days studied, with for instance lower energy consumption on weekends than on weekdays and higher peak power demand in Germany than in the other countries studied.

Once the travel data has been selected, BEV mobility modeling is divided into three steps. First, the key parameters and assumptions on the fleet of EVs and driver behaviors must be set. Second, a mobility algorithm calculates the charging demand for ‘uncontrolled charging’ of those vehicles. In addition, a smart-charging algorithm can then be used to compute the load curve for the corresponding fleet of EVs under different charging schemes: time-of-use tariff charging, unidirectional smart charging or V2G. This framework for electric mobility modeling is synthesized in Figure 2.1.

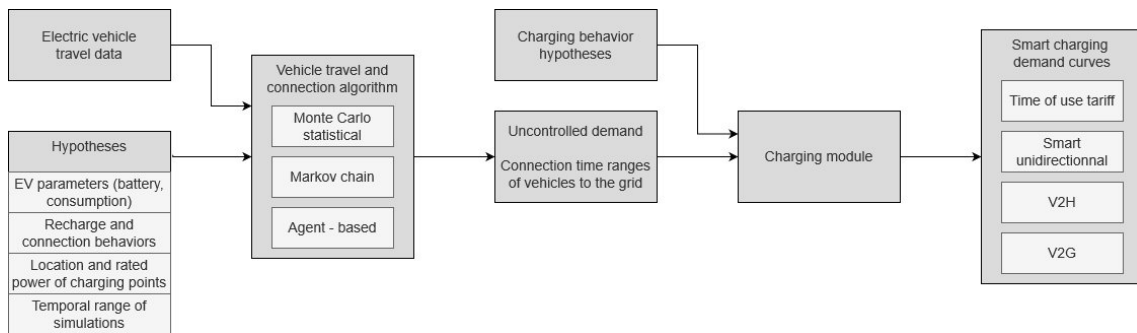


Figure 2.1: Electric mobility modeling framework

Among what is called in the literature *mobility modeling*, we will focus in this Chapter on models that generate EV load curves and connection to the grid data, based on individual vehicle usage.

This section starts by introducing travel data usage in mobility modeling. We then outline the scope of published mobility models in subsection 2.2.1 and go on to discuss the main algorithm approaches in subsection 2.2.2.

2.2.1 Scope and data

Travel survey data usage

Some models use raw data from travel surveys as inputs, whereas others need the data to be processed in the form of histograms, probability distributions or transition matrixes. Machine learning techniques can also be used to generate mobility data.

It appears that the distribution of departure times for the first trip of the day of EV users commuting to work is close to a Gaussian distribution (Borne et al.,

2018; Codani et al., 2015) whereas daily distances driven follow a log-normal distribution (Borne et al., 2018; Domínguez-Navarro et al., 2019) or also approximately a Gaussian distribution (Codani et al., 2015; Jarvis & Moses, 2019; Mehta et al., 2018; Yang et al., 2018). The arrival of BEVs at a charging station could also be modeled with a Poisson distribution (Domínguez-Navarro et al., 2019; Jarvis & Moses, 2019). Tamor et al. (2013) suggest a more complex distribution for daily distances driven (a weighted sum of exponential and normal distributions), which better fitted the vehicle trip dataset studied. Plötz et al. (2017) compared the distributions computed for four different datasets and found that the best distribution (between lognormal, Weibull and gamma) differs from one dataset to another.

Other studies create histograms from travel surveys as input data to their model (Bowman & Ben-Akiva, 2001; Darabi & Ferdowsi, 2011; Pasaoglu et al., 2013; Tan & Wang, 2014).

Another simulation method uses machine learning techniques on travel survey data in order to compute parameters of equations that model mobility (Arias & Bae, 2016; Rolink & Rehtanz, 2013). Apart from the support vector machines used by Arias and Bae (2016), Amara-Ouali et al. (2021) review the EV modeling approaches from a different perspective (matching EV models and datasets), and identify that random forests and artificial neural networks as other machine learning techniques that can be useful for EV load models. However, these machine learning models are less transparent and mainly relevant in the short term, with limited evolution of mobility behaviors. A further limitation of machine learning techniques comes from the need to determine whether the model should be trained to predict the power demand very accurately at peak demand or whether all simulation time-steps are equally critical in terms of accuracy.

From vehicle data to EV data

A common assumption made in most models in the literature is that EV owners would reproduce the same driving behavior as if they had an ICEV. This means that the data collected by travel surveys on a population mostly composed of ICEVs is selected as the input to model electric mobility. Even though total cost of ownership (TCO) considerations may lead the drivers that drive their car the most to switch to an electric one earlier (BEV in most cases, PHEV if they significantly use their car for long trips; Hagman et al., 2016), most vehicle usage data available today are surveys on ICEV drivers.

It seems difficult to prospectively quantify how much electric car usage will differ from today's ICEV usage patterns. Some authors investigate the research question of individual vehicle usage evolution when switching to an EV.

First, Palmer et al. (2018) reviews TCO comparisons between EVs, PHEVs and ICEVs in several areas of the world, and models EV adoption in Japan, the UK, Texas and California, each with different annual mileages, fuel prices and EV subsidies. This publication shows that for every region studied and sensitivity analysis on those results, the running cost of EVs is lower per km compared to ICEVs of the same vehicle class. Indeed, once an EV replaces an ICEV, there may be a 'rebound

effect' that increases the distance traveled per day. On the other hand, in some urban areas, the transition towards more public transport and shared mobility may lower the usage of personal vehicles.

Second, a few pilot projects led by car manufacturers on EVs involve data acquisition on real-life daily usage by a set of volunteer electric car owners. Ashtari et al. (2012) used the location of a set of 76 ICEVs which they described as "a statistical population best representing the drivers" of the area studied. Neaimeh et al. (2017) used data collected on two demonstrator projects (The EV Project and RCN) amounting to a total of 84 private electric cars (all of them based in the UK) monitored for the study. It emerged that males (90% of the volunteers), the 30–50 age range and high-income individuals were greatly over-represented in the study. Black and Nicholas (2018) describe another pilot project, held in a military base in California, where 29 EVs provide frequency regulation services to the Independent system operator through V2G.

Golob and Gould (1998) showed the bias that can occur when gathering EV trial data, with some users potentially changing their behavior during the trial period. However, these real-world data could be relevant for modeling EV user behavior when ICEV owners switch to an EV. They also point out that survey answers given sometimes differ from what respondents do.

A limited set of early adopters may not be significant enough to quantify the differential between EV and ICEV vehicle owners regarding daily distances driven, time of plug-in and EV owner localization (urban, suburban or rural), but it could give insight into how EV drivers will behave in terms of connection to the grid and charging patterns (Schäuble et al., 2017).

Furthermore, the limited range of most EVs implies that, unlike with ICEVs, long-distance trips (of a few hundred kilometers) must be completed with one or several mid-trip charging sessions, potentially at fast-charge stations. On the other hand, after short commuting trips, EVs will tend to be charged at home or at public low or medium power charging points. As a result, given that the charging approach for EVs differs from local commuting to long-distance trips, these trip categories could be distinguished to properly model EV charging patterns.

Main modeling parameters

When it comes to modeling a fleet of plug-in EVs, there are choices and assumptions to make on what to simulate from the diversity of vehicles, EV-user plug-in behavior, charging station nominal power, availability, and location. Moreover, EV consumption is temperature-sensitive (higher power consumption in a low-temperature environment due to electric heating and slightly higher consumption in a high-temperature environment due to air conditioning; Yuksel and Michalek, 2015), and mobility needs differ between a working weekday and a weekend day, and between periods of the year, so the time range of the simulation has to be selected accordingly.

Types of vehicles modeled In 2020, the IEA identified a cumulative total of more than 360 EV, plug-in hybrid electric vehicle (PHEV) and BEV models available on the market (IEA, 2021), constituting a wide range of battery capacity, consumption and maximum rated power for grid connection. However, most studies select only one of these vehicle types and consider the EV fleet to be composed of copies of that car model. Other studies do not even take into account battery capacity and consider that each EV has a large enough battery to cover all its trips each day and charges the energy consumed during that day before the first trip of the following day (Alonso et al., 2014; Bowman & Ben-Akiva, 2001; Galus et al., 2012; Mullan et al., 2011).

A more diverse EV fleet can be found in Chiche et al. (2017), Mehta et al. (2018), Pasaoglu et al. (2013), Soares et al. (2011), and Weiller (2011). Taking into account a wider range of vehicle types (PHEVs and BEVs with different battery capacities) induces longer simulation times and more complex input data, but may prove relevant to investigating how much the results of studies on smart charging and V2G are sensitive to the composition of the fleet.

In order to evaluate the impact of the electric mobility sector on power systems, it seems necessary to study the charging behavior of all types of EVs simultaneously (PHEVs, city BEVs, sedan BEVs and luxury BEVs). The charging of a large number of low-capacity PHEVs may affect the value for the electrical system of smart charging large BEVs. Larger batteries (typically more than 50 kWh) mean higher smart charging and V2G potential, but also users that may not connect their vehicle to the power grid every day. Small batteries (less than 30 kWh) may imply daily charging and therefore synchronization of peak power demand.

Charging and connection behaviors modeled Most studies on V2G consider that each vehicle is connected when parked at a place where a charging point is available. However, the trajectory of growth in battery capacity and vehicle autonomy implies that many drivers will not need to recharge their EVs every day to meet their mobility needs. As a result, studies on the charging of EVs (Alonso et al., 2014; Bowman & Ben-Akiva, 2001; Darabi & Ferdowsi, 2011; Grahn et al., 2013; Jarvis & Moses, 2019; Lojowska et al., 2012; Rolink & Rehtanz, 2013; Shahidinejad et al., 2012; Yang et al., 2018) also simulate drivers that only connect every few days, when their battery charge drops below a given threshold.

Regarding smart charging, even if the optimal load pattern on a week of simulation may sometimes mean postponing EV charges to the following day, most studies consider that when a driver connects their vehicle to the grid, they want, if possible, to start their next trip with a fully-charged (or >90%-charged) battery (see for instance Dallinger et al., 2011; Hodge et al., 2011). This constraint, considering EV owners' charging-pattern behaviors, may reduce the benefit of smart charging if the simulation time range is long enough.

Charging points modeled Currently, along the development of EVs in the world, charging points are being built in various environments. According to

IEA (2019) and Spöttle et al. (2018), the European Commission recommends one public charging point for every 10 EVs in the fleet. France, for instance, follows this recommendation, as there was 25,000 installed public charging points for around 250,000 BEVs and PHEVs in early 2019². Among those public chargers, more than 75% are installed in public locations (i.e. public car parks and city-centers) with the rest in industrial or shopping-center car parks. Each charger has a maximum rated power at which the EV can recharge. The maximum rated power of most public chargers is between 7 kW and 40 kW, but highway service stations are currently being equipped with fast chargers up to 350 kW (Domínguez-Navarro et al., 2019). If equipped with a private parking spot and a power socket, EVs can also be recharged at home at between 3 kW and 7 kW (in France, rated powers may differ from a country to another) depending on socket type. It is to be noted that not every EV battery can be charged at a fast charger (especially small batteries).

Some EV load models focus on only one type of charging point, and many of them only take into account residential charging, a key assumption being that every EV user has access to a charging point at home on a private parking spot and never recharges their vehicle elsewhere (Alonso et al., 2014; Codani et al., 2015; Dallinger et al., 2011; Grahn et al., 2013; Mullan et al., 2011; Soares et al., 2011; Tan & Wang, 2014). Results from most of these studies show charging occurring mainly at night, while the vehicle is parked at home. This kind of assumption is suited to studying the aggregation of EVs for smart charging (including V2B and V2G) or the integration of EVs in smart grids or distribution grid systems. Other studies aim to evaluate the grid integration of public charging stations (Domínguez-Navarro et al., 2019; Iacobucci et al., 2018) where EVs can charge throughout the day.

On the other hand, some models are capable of simulating EV users who can recharge their vehicle at different locations and possibly at different power levels (Chiche et al., 2017; Druitt & Früh, 2012; Steen et al., 2012; Weiller, 2011). Nonetheless, these models require assumptions to decide where and when an EV will be charged when a charger is available at various locations (home, work and public chargers for instance). In order to go into further details about EV modeling from a charging infrastructure operator point of view, see the literature review work of Metais et al. (2022).

Temporal range of simulations

Most BEVs sold today have a battery capacity between 40 kWh (i.e. Nissan Leaf) and 100 kWh (i.e. Tesla model X), which means an autonomy of a few hundred kilometers. Moreover, car manufacturers are conceiving electric cars with larger and larger driving ranges, as range anxiety (along with price and the need for charging points) is identified as one of the main barriers to further development of electric mobility (Vassileva & Campillo, 2017).

²However, one should keep in mind that this 1 charge for 10 EV recommendation is arbitrary, and the ideal EV/charger ratio depends on the density, share of individual housing and other parameters.

The driving range of the average EV meets the mobility needs of an average driver for a period of a few days, which means that not every electric car needs to be recharged every day. However, much of the scientific literature studies the behavior of electric car drivers using 24h-long simulations. Even though mobility needs differ for working days and weekends (Druitt & Früh, 2012; Pasaoglu et al., 2013; Soares et al., 2011), many papers aggregate working days and weekend travel survey data (Alonso et al., 2014; Darabi & Ferdowsi, 2011; Lojowska et al., 2012; Tan & Wang, 2014).

Soares et al. (2011) reports that 24% of EV drivers surveyed plug their vehicle into the grid “when convenient and the driver has time”, and 23% charge “only when needed”. As a result, a part of the fleet is not recharged with the same probability every day and is recharged more frequently on weekend days than on working days. A more complete and accurate temporal model of mobility needs can be gained using longer simulation time periods and distinguishing between working days and weekend, as attempted by Pasaoglu et al. (2013).

Once the input data (freshly created or from a national travel survey) has been gathered and the scope of simulation (in terms of types of vehicles, charging patterns, charging points, size of fleet, etc.) has been defined, the algorithm part of the model processes the input data in order to compute the temporal mobility needs. The section below reviews the options for algorithm architecture.

2.2.2 Algorithm structure approaches

Several simulation methodologies can be found in the literature. Daina et al. (2017) classified these models into three main types: activity-based modeling (ABM), direct use of observed activity–travel schedules (DUOATS) and Markov chain models (MCM). In fact, the type of model often reflects the field of research the model is used in. This section presents the model classes and the studies they are mainly used for, and the qualities and specificities of each model class are highlighted.

Monte Carlo statistical models

Monte Carlo statistical models (MCSM), corresponding to DUOATS introduced previously, rely on travel-survey data in the form of probabilistic distributions or histograms. The relevant data for such models are statistics on distances driven and departure times. After assumptions have been made about the size of the EV fleet and which vehicles, charging points and charging locations to model, MCSM independently simulate each vehicle in the fleet.

For a given vehicle, a distance and a departure time are randomly generated from the corresponding distributions (Monte-Carlo simulation). Based on these parameters, the algorithm derives the temporal period when the vehicle is connected to the grid. In most studies, all these parameters are generated independently from each other. Moreover, MCSM models are scalable: if a large enough fleet of EVs (in terms of diversity in the input data) is simulated, then the demand data of a significant EV fleet of another size can be computed proportionally.

Macro-MCSM models for fleet aggregation studies The MCSM approach is commonly used for EV aggregation studies when only the total power demand for the charge of an EV fleet is required. Some papers working under assumptions introduced previously study the impacts of an aggregated fleet of EVs on power grids. Codani et al. (2015) applied the MCSM approach and averages for 100 Monte Carlo simulations of 100 vehicles, and Borne et al. (2018) simulated a fleet of 3000 vehicles in order to assess the potential of EV usage for frequency regulation.

Wu (2018) designed a slightly different approach. Instead of randomly generating travel data, their algorithm uses five pre-built mobility patterns. One of these patterns is selected for each vehicle, and then an uncertainty value is generated from normal distributions for the departure time, arrival time and daily mileages in order to account for the randomness of EV connection to the grid. Dallinger et al. (2011) modeled a fleet composed of PHEVs and BEVs. To ensure their algorithm simulated PHEV and BEV behaviors similarly, they modified the daily distances histogram of PHEV so that it only generates the distances driven in electric mode.

Some other models of the literature do not change the histogram for PHEV and apply a coefficient of distances driven in full electric mode. The MCSM approach was used on different EV fleet sizes: by Steen et al. (2012) to set fleet size according to the distribution grid typology, and by Mehta et al. (2018) in a sensitivity study to determine the maximum fleet size connectable to an industrial car park, given network limitations.

Localized MCSM models for DSO and smart grid studies MCSM models are also well suited to studying the integration of EVs in smart grids. In addition to randomly generating (from histograms or distributions) departure times, arrival times and daily mileages, some models also generate the localization of the parking spot of every vehicle modeled, so that local curves can be derived.

Neaimeh et al. (2017), for instance, randomly selected EV owner connection points in a distribution network based on data on the residential topology of the area. Similarly, Jarvis and Moses (2019) applied the same methodology for multiple EV fleet sizes across the area studied. Jiang et al. (2014) assigned each transformer a number of EVs proportional to the population connected to that transformer, and then randomly selected in-area households possessing those EVs.

Apart from methodologies to generate the location of EV owners, research has also studied EV diffusion in the population based on socio-economic parameters (Gnann et al., 2018; Ramos-Real et al., 2018). It has been shown that market diffusion trends differ from region to region and that income level, environmental concerns and charging infrastructure available are key parameters driving willingness to change to an EV.

Travel distance-departure time correlation MCSM models Some models try to go beyond the approaches presented above, by keeping the correlation between travel data in the survey results instead of randomly selecting all the parameters of the trips of a given car (daily mileage, departure time, arrival time,

localization, consumption) independently.

For instance, Grahn et al. (2013), Hodge et al. (2011), Jiang et al. (2014), Mullan et al. (2011), and Wu (2018) focused on correlating EV arrival times and the times plugged into the grid with local residential electricity consumption, which gives a more realistic study of distribution grid electricity flows along the EV development trajectory. Uncontrolled EV charging was found to induce higher peak loads on power grids than in simulations with independent arrival times and residential consumption. On the other hand, Ashtari et al. (2012), Lojowska et al. (2012), and Tan and Wang (2014) studied the correlation between distances driven and trip departure/arrival times of travels. The section below outlines the rationale and methodologies for taking this correlation into account in electric mobility modeling.

According to a study on data from the French national travel survey (SDES, 2019), distances driven (in France) over a whole day are negatively correlated to first departure time of the day and also positively correlated with arrival time at home (Figure 2.2). Lojowska et al. (2012) reached the same conclusions using data from the Dutch National travel survey. Ashtari et al. (2012) also found (using US National travel survey data) that the daily distances driven by EV users leaving early in the morning (6pm–7pm) are higher than those of the whole dataset.

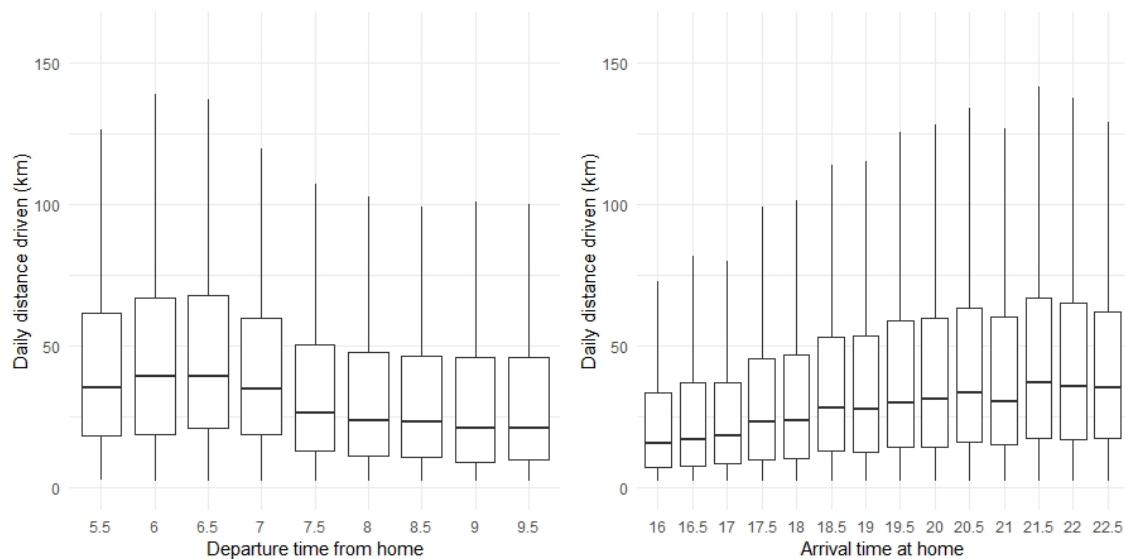


Figure 2.2: Daily mileage/departure and arrival time correlation. Data from (Ministère de la Transition Ecologique et Solidaire, 2008)

The methodology used in Ashtari et al. (2012) is based on pre-processing the travel survey data in order to generate additional conditional histograms to serve as input data to their algorithm. Instead of a global daily mileage histogram for each trip, they processed many daily mileage histograms with each one corresponding to a range of departure times. They also populated the algorithm with more arrival time histograms with each one corresponding to a departure time,

daily mileage range.

Tan and Wang (2014) applied a different method to generate travel parameters for a given vehicle. To begin with, departure and arrival times from the residential parking spot of vehicles were considered as “two independent events”. Departure times and arrival times were each divided into 5 classes from “very early” to “very late”, and daily mileages were divided into 5 classes from “small” to “large”. From the input data, a 5X5X5 Matrix is then built that contains the conditional probability that a daily mileage belongs to the distances class d , given that the departure time belongs to the dep class and the arrival time belongs to the arr class.

The main advantage of this approach compared to Ashtari et al. (2012) is that the algorithm is more efficient when based on a smaller input travel data volume, but it does require much more data processing beforehand.

Lojowska et al. (2012) investigated the dependency between daily mileages, departure times and arrival times. They applied a more mathematical approach based on copula theory (applied to the energy sector, as described in Papaefthymiou and Kurowicka, 2009) that computes a correlation matrix between the variables studied. As they found a significant correlation between the travel data of two consecutive home-to-home trips on the same day, they separated the input data into two groups: daily single home-to-home trip and double home-to-home trips. For each group, they generated a normal copula multivariate distribution function, and the simulations followed the principles of MCSM, where departure time, arrival time and distance traveled are generated from the corresponding multivariate distribution function.

Specific MCSM models Liu and Etemadi (2018) follow a different approach for modeling EV charging demand. Based on travel survey data, a driving profile vector was derived for each respondent, composed of the distance driven on each time-step of the day. A k-means clustering algorithm is then used on those vectors to generate a limited set of mobility profiles (selected as the centroid of each cluster). To model charging behavior, instead of a stochastic process of randomly generating travel data from each EV, the charging algorithm processes the data of the mobility vector clusters. This approach implicitly accounts for the correlation between daily mileages, departure times and arrival times, and it is also computationally significantly faster than most mobility models introduced in this Chapter (as only a limited set of representative mobility profiles are processed).

Markov Chain models

Markov chain models (MCM), as introduced by Soares et al. (2011), follow a different approach. Instead of relying on random selections of daily mileages and departure times for each vehicle, the input data takes the form of transition probabilities. This methodology models vehicles using “states”. For each vehicle, a time vector composed of the state of the vehicle is computed. Soares et al. (2011) introduced the following states: in movement; parked in a residential area; parked in an industrial area; parked in commercial area.

The simulation of the charge of an EV fleet follows a single rule after initialization of the states of every vehicle for the first time step of the simulation time range: the state of a vehicle at a given time step t is derived from the conditional transition probabilities of time step t , given the state of the vehicle at time step $t-1$ (principles of a Markov chain).

Rolink and Rehtanz (2013) designed a mobility model that follows the same principles but with a semi-Markov process approach that includes sojourn times in addition to state-to-state transition probabilities in the algorithm input data. Their model tends to address two limits of the Soares et al. (2011) model: the coherence between all trips in a day for a given vehicle, and the distribution of the duration of a vehicle being parked at given areas.

Grahn et al. (2013) also built a MCM, but in addition to state of the vehicle, they also studied the state of the EV owner and they added residential patterns. They decompose the state “parked at home” into several possible states: “sleeping”, “cooking”, “washing”, “TV”, and so on. Hence, the total residential curve can be derived for every individual studied, including EV charge but also powering other appliances. This model needs much more input data than previous models, including residential data which is out of the core scope of study of most other works on electric mobility.

In the literature, the Markov chain approach is mainly used for generating uncontrolled EV demand profiles that are separated according to charging point type (residential, commercial, work). Even if MCM model well the randomness of the behavior of EV owners and give additional information on localization of the vehicle (currently driving, at home, at work, parked at another location), they seem to be less common in the literature than Monte Carlo statistical models. This might be linked to their longer computation times (one random generation of state for each time-step of every vehicle) and the data processing needed before use, which might make them less suited for prospective or sensitivity studies.

Agent-based models

EV charging patterns can also be generated from agent-based or activity-based models (ABM). Agent-based models aim to model the whole transport sector, which means multiple means of transport with their modal shares considered, and road traffic is modeled so that car speed is slowed by traffic congestion. As described by Bowman and Ben-Akiva (2001), ABM consists in deriving trip demand from activity demand instead of taking trip demand data as an input of the model. This class of models, which are more complex than the approaches introduced in the section above, entails much longer computation times and a geographically limited area of study (typically a single urban area). In addition to travel data, the topology of the transport network needs to be added to produce a localized simulation. Additional data on agents’ activities, household locations and means of transport available are also necessary.

ABMs give more realistic results in terms of temporal coherence of agents’ travel patterns, and they can inform urban planning studies on the impacts of

transport infrastructure development (modal shift from personal vehicles to public transport) on the transport sector and more accurately model how new mobilities, such as shared autonomous vehicles, will affect mobility behaviors, and impact power systems (Iacobucci et al., 2018). ABMs in the transport sector literature include MATSim (Balmer et al., 2006) and TRANSIMS (Hodge et al., 2011), which are open-source programs for implementing agent-based use cases. Other authors have developed their own ABM (Bowman & Ben-Akiva, 2001; Iacobucci et al., 2018).

Algorithm structure approach	Input data required	Strengths	Weaknesses	Reference
Macro Monte Carlo statistical models	Travel survey data	Good accuracy for aggregated results of a large number of EVs, easy to implement	Provides average EV demand data for a large number of EVs that may not be derived at the local level	Borne et al., 2018; Lojowska et al., 2012; Steen et al., 2012
Localized Monte Carlo statistical models	Travel survey data, EV charger localization	Good approximation of localized EV demand at one location type with limited input data	Lesser accuracy on the localization of EV charge among multiple charger locations (at home, at work or public charging), compared to agent-based models	Jiang et al., 2014; Neaimeh et al., 2017
Markov chain models	Travel survey data	Enables the correlation of EV charge with other electrical appliances, models well the randomness of EV behavior	Additional travel data processing that does not improve results accuracy, compared to Monte Carlo statistical models	Grahn et al., 2013; Rolink and Rehtanz, 2013; Soares et al., 2011
Agent-based models	Travel survey data, Agent activity data (Optional : transport network topology)	Best approach for providing accuracy at the local level, multiple open-source software available, enables the study of the whole transport sector	Additional input data required, larger computational times, geographically limited area of study	Balmer et al., 2006; Bowman and Ben-Akiva, 2001; Huang et al., 2012

Table 2.1: EV modeling algorithm approaches comparison

Huang et al. (2012) and Iqbal et al. (2021) describe the four-step model, a subcategory of ABMs, also used for other transport modeling studies than EV development. In this approach, each trip computation is divided into the following steps: first, generating the purpose and the distance of the trip; second, generating the departure and target geographic locations; third, selecting the transport mode suitable for the trip; and fourth, computing the optimal path.

Beheshti and Sukthankar (2012) showed that ABMs (with additional survey data) are more accurate than MCMs for forecasting the occupancy of parking lots in a small study area. However, when the data is limited to 'realistic' data instead of extensive survey data, ABMs do not provide significantly better results than other modeling approaches.

At a larger scale, i.e. a country or a zone with tens of millions of inhabitants, ABM are quickly limited in terms of number of vehicles and size of the transport infrastructure network that can be modelled.

The model types presented in this section are summarised, along with their strengths and weaknesses in Table 2.1 and in Figure 2.3.

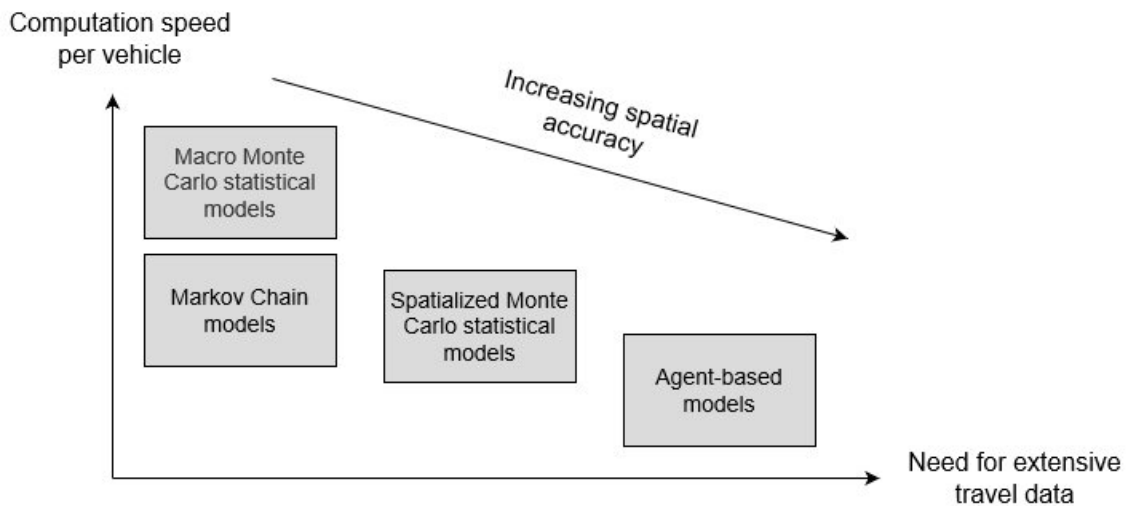


Figure 2.3: Comparison of mobility modeling approaches (in terms of computation speed and need for data)

2.3 Fitting BEV transport models into power system operator charge models

So far, we have only discussed modeling approaches that consider EV charging to be solely determined by traveling habits. However, such charging strategies, referred to as "uncontrolled charging", can impact power systems. Smart charging approaches have also been developed, not only to reduce the strain of EV charging on power system planning and operation, but also for EV charging to provide

value for the power system. Here we describe the motivations for optimizing EV charge loads, outline the charging approaches to be considered, and present the optimization methods found in the literature.

2.3.1 Charging approaches

The literature reports several ways that smart charging BEVs can deliver several services to power systems (Thompson & Perez, 2019):

- **Grid congestions.** EV charging could congest distribution and transmission grids and overload power converters, especially at peak demand times. Shifting the load of EVs towards a time when the network is less constrained is an efficient solution to limit grid congestion and reduce the need for investments to reinforce the power grid. To incentivize EV owners to do so, low charging tariffs at night seems to be the easiest option to implement (Alonso et al., 2014; Gonzalez Venegas et al., 2019; Hodge et al., 2011; Steen et al., 2012). Moreover, considering the development of decentralized solar PV generation, EV charging at midday could help solve grid congestion linked to peak solar PV generation.
- **Frequency regulation.** Network frequency needs to be kept close enough to its nominal value to avoid power grid crashes. To do so, frequency regulations systems, with their related markets, have been designed in most countries. EVs seem to be better geared to participating in frequency containment reserve (FCR) markets when they are aggregated into large enough fleets (Borne et al., 2018; Codani et al., 2015). Indeed, power related services, such as FCR, do not require the vehicle batteries to provide much of their energy stored. As a result, the depth of discharge of the vehicles providing FCR is limited, and so is the cycling degradation of the vehicle battery (Thompson & Perez, 2019).
- **Voltage regulation.** Power networks also have to deal with voltage drops, especially at peak load, and voltage rises, especially at peak generation, in distribution grids. However, few studies have focused on EV contribution to address this problem (Yong et al., 2015).
- **Supply and demand adequacy.** Controlling EV charging load is also seen as a way to provide demand-side management to balance power systems (Druitt & Früh, 2012; Liu & Etemadi, 2018; Pantos, 2012). Shifting EV charging times could help correlate charging sessions with the lowest hourly electricity prices possible, and thus reduce charging cost for EV owners.
- **Distributed energy resources (DER) coupling/local consumption.** Along with promoting EVs, governmental incentivization also promotes the development of photovoltaic panels in order to reduce the carbon footprint of the energy sector. As a result, a share of EV owners might also become

“prosumers” with solar panels on the rooftop of their house. The synergy between photovoltaic generation and EV recharging is described in Clastres et al. (2021) and Hoarau and Perez (2018). Smart bidirectional charging could then be used to enable these users to maximize the share of their locally-generated power used to power their house and their vehicle, storing energy at midday in the battery of their EV and discharging it back into their house at peak demand in the evening (Domínguez-Navarro et al., 2019; Eid et al., 2016; Wu, 2018).

Several charging approaches have been studied and developed in an effort to address the key power system challenges. From the most basic to the most complex, the approaches to be considered when building a mobility model are:

- **Uncontrolled charging**, the base case for most studies, in which the EVs recharge to full state of charge, at maximum power, as soon as they are connected to a charging point.
- **Time-of-use (TOU) tariff charging**. TOU tariffs consist in applying lower electricity tariffs in off-peak periods, which is the simplest way to incentivize EV owners to delay the charge of their vehicle so that no additional power is taken from the power system at peak time. In order to avoid simultaneous demand increase from all TOU tariff users, a low tariff hours signal is sent with a different time offset to different user groups. Two key advantages of TOU tariff schemes over other smart charging approaches is that they need less infrastructure and are more easily accepted. In fact, they only require an electrical device that receive time-of-use on/off signals or a smart meter, which are currently being rolled out in most developed countries.
- **Smart unidirectional charging**. Smarter charging patterns other than TOU charging have been studied (Galus et al., 2012; Liu & Etemadi, 2018; Weiller, 2011; Yang et al., 2018). They belong to the same group as TOU charging as they rely on delaying the charge of the EV towards periods when market prices are lower or when the generation mix is less carbon intensive. However, they require a communication device between an EV charging aggregator agent and the electricity meter, charging point or EV. The EV owner should provide the information of the expected departure time of their next trip to ensure that their vehicle will be sufficiently charged. The aggregator can then manage the charging constraints of every vehicle in their fleet to minimize fleet charging costs and even provide other flexibility services in the electricity markets (Hodge et al., 2011; Liu & Etemadi, 2018).
- **Smart bidirectional charging**. V2G, as introduced by Kempton and Tomic (2005), is considered the EV charging approach that maximizes the flexibility provided to power system by electric vehicles. It works in much the same way as smart unidirectional charging, except that the charger used is bidirectional (and thus, more costly than unidirectional charging points). As a

result, the vehicle can discharge its battery to enable more flexibility to the grid, for instance by flattening the residual load curve (Alonso et al., 2014), generating electricity when prices are high, for balancing its power systems (Druitt & Früh, 2012; Pantos, 2012) or providing frequency regulation services (Borne et al., 2018; Codani et al., 2015; Tan & Wang, 2014). Another charging approach that uses bidirectional chargers is vehicle-to-home (V2H) or vehicle-to-building (V2B), where the bidirectional charger is used to provide electricity to the building. Depending on the tariff structure selected, powering the building with the EV battery when electricity market prices are too high can reduce overall electricity expenses. When coupled with solar panels, V2H/V2B can also maximize the share of local energy consumed by the building.

	Time-of-use tariff	Smart unidirectional	V2H/V2B	V2G
Grid congestion	X	X	X	X
Frequency regulation		X		X
Voltage regulation			X	X
Supply and demand adequacy	X	X	X	X
Local DER coupling			X	X

Table 2.2: Charging approaches suitable for flexibility provision

2.3.2 Optimization problem formulation

Modeling how smart charging will be implemented starts by setting an optimization problem, and often additional data needs to be added. Some studies focus on optimizing the whole system, while others focus on individual actors that aim to minimize their costs. The following sections describe the optimization objectives and problem formulations found in the literature.

In most approaches, all EVs are aggregated as one virtual battery in the optimization problem, while the required state of charge, connection time and disconnection time take the form of constraints in the optimization algorithm. However, Pantos (2012) split the EVs in their simulation into several fleets with similar mobility behaviors. As a result, mobility constraints are more precisely considered, and it becomes possible to identify which mobility behavior group has the greatest value in the electricity markets.

Power grid sizing optimization

A share of the models studied focus on minimizing the impact of EV recharging on grid reinforcement costs. These studies do not take electricity market data into account but instead add the EV load generated from their mobility model to residual consumption (consumption minus local renewable generation) of the area studied. This makes it possible to study the impacts of EV charging on the sizing of distribution grids and converters (Hodge et al., 2011; Mehta et al., 2018; Wu, 2018) and to implement smart-charging techniques to minimize these impacts (Alonso et al., 2014; Mullan et al., 2011). V2G could even be used as a peak-shaving solution (Alonso et al., 2014; Galus et al., 2012; Tan & Wang, 2014). He et al. (2013) described a methodology for coupled optimization of transportation and power networks in a static time framework. Further progress hinges on gathering enough data to extend this methodology to several-day simulations and using more diverse electricity generation mixes with intermittent energy sources.

Price-based optimization

Many studies focus on valuating smart charging approaches from the consumer point of view or the whole power system point of view. In theory, aggregators attempting to minimize the charging cost of their fleet from the spot market would need a price forecasting model. However, most smart charging modeling studies have used either historical annual average spot market price data (Borne et al., 2018; Codani et al., 2015; Pantos, 2012) or historical data on selected days (Domínguez-Navarro et al., 2019). The main limitation of selecting historical market data to evaluate savings through smart EV charging is that EVs are implicitly considered price-takers on the market. This is a reasonable assumption for studying the introduction of a few EVs. Nevertheless, for prospective studies where EV charge becomes a significant share of total consumption, the impact of EVs on prices (as well as on gas supplies in the current context) might not be negligible.

To go beyond using historical data for EV charging studies, Dallinger et al. (2011) and Druitt and Früh (2012) used a market model (production cost model) that simulates which power generating units will be producing electricity during the simulation (including ramping constraints, minimum power and minimum up-time constraints of some of the generators). These production-cost model simulations found that larger EV fleets participating in electricity markets implies lower smart-charging revenues.

Specific optimizations

A few other models mention other optimization algorithms than those described in the previous subsections. Steen et al. (2012) showed that price-optimal and network-optimal load curves differ strongly from each other and from the uncontrolled load curve. As a result, a gap to address in the literature is simultaneous network and price optimization, potentially with network limitations as a hard

constraint and price minimization as a soft constraint in the optimization algorithm. As stated in this section, many services to power systems can be provided by electric vehicles, through different charging approaches. Here we outline the key smart-charging modeling approaches and establish the link between methods used and studies performed. The following section focuses on guidelines for using charging methodologies.

Smart charging optimization point of view	Strengths	Weaknesses	References
Network-based	Evaluate the impacts of EV charge on the power grid reinforcement needs	Need data and modeling of the electricity network considered	Hodge et al., 2011; Mehta et al., 2018; Wu, 2018
Peak-shaving	Minimize reinforcement costs of transformers, easier to implement than a network simulation	The local optimum of EV smart charging might differ from the global optimum	Alonso et al., 2014; Galus et al., 2012; Tan and Wang, 2014
Historical market price	Strong analysis of EV charging costs as price-taker, easily accessible market data	Not suited for long-term prospective studies	Borne et al., 2018; Pantos, 2012
Production cost model integration	Enables the analysis of EV diffusion in various generation mix evolution scenarios, evaluate the effects of EV smart-charging on prices	Necessary to gather software and data for power system modeling	Dallinger et al., 2011; Druitt and Früh, 2012

Table 2.3: Optimization approaches for EV smart charging

2.4 Model use cases

We have reviewed the scientific literature on mobility modeling approaches and methodologies. Next, we turn to identify the approaches best suited to the studies of EVs. First, we describe the modeling approaches recommended for large-scale studies of EVs (TSOs and big aggregated EV fleets). Second, we focus on more local studies from a smart grid or distribution system operator perspective. Third, we give the recommended modeling approaches for other specific study topics found in the literature. The recommended model characteristics for each study topic presented are summarized in Table 2.4.

2.4.1 Mobility model requirements for transmission system planning issues

Transmission System Operators (TSO) manage electricity transmission systems and are in most countries responsible for the generation-load adequacy. TSOs conduct prospective research to guide the development of their network and the power generation mix, and the impact of EVs on their systems are being studied (RTE, 2019). Rious et al. (2011) showed that forecasting connection of energy resources to the grid helps to reduce the investment needed to adapt the power network, by adopting a proactive behavior, given the investment dynamics to upgrade the power grid. For long-term studies, TSOs may need to evaluate the sensitivity of optimal investment strategies to the size of the EV fleet, the evolution of battery capacities, and the share of EVs adopting smart-charging technologies (RTE, 2019). The method required of a TSO study thus becomes an EV charging model that considers a mix of vehicles, charging strategies, rated power and charging locations. On top of that, studies on power flows need to derive local load curves from the global load curve. This TSO-scale geographical approach is not well covered in the electric mobility modeling literature.

Recommended approaches for transmission system mobility modeling

When a national travel survey is available, it is often the best data source available for trip characteristics (departure times, distances driven) at a national scale. Data from demonstrator projects could also be added. If possible, departure time–arrival time and daily mileage correlations should be considered for greater accuracy. As seen above, modeling the whole electric mobility ecosystem of the zone studied is advised, and thus study as many vehicle types, battery capacities, charging points, connection behaviors and mobility profiles as possible. Moreover, they should aim to distinguish between local trips and long-range trips. For those reasons and given the scale of the study zone and the size of the fleet to be modeled, Monte Carlo statistical modeling emerges as the best suited modeling approach for TSOs.

Simulations can also be run on an annual time range to capture the temperature-related sensitivity of EV consumption and annual patterns of local trips (between working days, weekends and holidays) and differentiate long-distance trips according to annual travel activities (economic and touristic). Departure times/daily mileage correlations can be studied to achieve more accurate results. Finally, for some specific network studies, more local load curves are necessary, either via a top-down approach, which means building a distribution key to downscale the national load curve, a bottom-up approach, based on dividing input data into several specific zonal subsets, or a combination of bottom-up and top-down approaches. One of the gaps that TSO studies need to address is the integration of electric mobility in a realistic and complete model for the entire electrical system.

Recommended approaches for other aggregated fleet modeling studies

As stated earlier, much of the scientific literature focuses on estimating the value of EV aggregation on electricity markets. Like TSO models, aggregation studies need good temporal accuracy, which implies that an ideal model for EV aggregation studies would use Monte Carlo statistical modeling on data from a national travel survey, potentially considering departure time/daily mileage correlation. Longer simulation time periods than daily simulations and precise market data are also advised. However, for this type of study, it is often reasonable to run a case study on local mobility with a single charging point location (residential) and a single maximum rated power of charging points, working to the assumptions of systematic connection of EVs to the grid.

Furthermore, historical price data is an appropriate input to price-based optimization for smart-charging algorithms when studying the short-term impacts of EVs on power systems. However, a more complex market simulation tool is recommended for prospective long-term studies (with high shares of EVs) in order to account for the impacts of EVs on electricity prices³. Additionally, another issue to address in EV fleet aggregation studies is aggregator behavior in an uncertain future and in competition with other aggregators. Both these topics require additional game theory or uncertain market models, which we have not covered here.

2.4.2 Model use case: A smartgrid/distribution system perspective

Recommended approaches for a EV / other DER coupling adequacy study

The flexibility tied to EV charging is often seen as a way to maximize the share of locally-generated electricity used in a given community. The requirements of a mobility model to study this kind of setting depend on the target zone. For instance, when studying a residential neighborhood, it may only be necessary to compute residential charging (at a single rated power) for local mobility trips. Indeed, EV owners in an area with a high usage of other DER (especially photovoltaic panels and stationary batteries) are incentivized to connect and charge their vehicle as much as possible on chargers within the area, in order to get the most out of their DER equipment. Moreover, the study should also account for the correlation between solar panel ownership and electric car usage, if such data is available. Consequently, either agent-based or Monte-Carlo modeling seems to be suited for these studies, each with their strengths and weaknesses, as identified in section 2.2. Ultimately, the optimization algorithm aims to highlight local-scale synergy between EVs and other DERs (photovoltaic panels, other distributed generation systems). In case the neighborhood where a smart-grid is implemented

³We can expect that load shifting from peak demand times to time periods when marginal generation technology is less costly will result in lower prices at peak times, and lower overall operating cost of the electric system than uncontrolled charging (RTE, 2019)

is fully residential, most EVs might not be connected during peak solar production around mid day, so stationary batteries might be necessary to complement PV generation.

Recommended approaches for network and power flow analysis

Studying flows on the power grid implies a computation of total consumption, which means that EV demand has to be added to electricity consumption by other electrical appliances. Moreover, a load curve must be derived for each household in the area studied, as an input to the distribution grid power flow algorithm. Here, ABM is the most suitable way to generate mobility behavior with good spatial accuracy and in a city-scale system. EV connection time ranges could also be derived from the residual residential consumption data, which can be done by correlating the surge in residential consumption with EV arrival times (Grahn et al., 2013). Multiple charging behaviors and smart charging modes could also be applied. Finally, in the EV smart charging algorithm, power flows on the grid must be the major constraint, but price data could be added as a secondary soft constraint to model how aggregators would manage the charging of their fleets.

2.4.3 Model use case: Other specific perspectives

Other types of case studies on electric mobility require specific mobility modeling. Studies on the development of autonomous cars in cities (Iacobucci et al., 2018) or public charging networks require a specific focus on the spatial position of recharge needs and the maximum power demand. This makes ABM the most suitable approach, as it thoroughly accounts for spatial accuracy and coordination of the vehicles of the fleet in order to match mobility needs. Furthermore, it may be advisable to model diverse charging power, as vehicles may be recharged quickly if their next trip is urgent but slower if their next trip is not for a few hours. Finally, week-long simulation with specific data for each day is recommended in order to capture the specificities of each day of the week in terms of peak travel demand time and intensity.

The methodologies for locational optimization of public charging infrastructure, which is not the core topic of this document, are reviewed in Shen et al. (2019).

Studies on sizing highway fast chargers require a specific dataset (either long distance travel survey or highway traffic data) in order to evaluate mid-trip charging needs for long-distance EV travel. Here we recommend MCSM with a spatial derivation of the global results from highway traffic data.

Additionally, from a policy maker perspective, studies on incentivizing either public EV charging network, or higher battery capacities require mobility modeling of the usage of public charging points, either globally with MCSM or spatially (at the scale of a conurbation) with ABM.

Finally, some studies address EV charging demand at specific industrial or commercial car parks, possibly in interaction with DERs. For these studies, the focus

should be on implementing the right constraints for the optimization algorithm in terms of time spent in the car park, based on the travel data available. Correlation between distances driven (and thus energy needed) and arrival times could be studied for further accuracy. Multiple EV types (BEVs, PHEVs), battery capacities and charging behaviors should also be studied in order to model the diversity of EVs potentially recharging in the car park studied.

2.5 Conclusion

This Chapter reviewed the approaches employed in the EV charging literature regarding input data, assumptions, mobility modeling and load management modeling. The electric mobility literature has amply studied and documented local models focusing on a small area with high spatial accuracy and global models producing aggregated results with good temporal accuracy. However, there are still gaps that leave room for improvement in terms of EV modeling.⁴

First, a common limitation of many EV studies is the lack of reliable data on EV trips and charging behaviors. Most of the data currently used comes from national travel surveys, which in fact consist mainly of ICEV data. EV behavior could differ from ICEV usage. This lack of data may soon be filled via increased collaboration between car manufacturers, transport infrastructure companies, telecom companies, other industry players, and academics. More feedback data on EV usage would also help on this topic. Moreover, pilot project data on real-life EV usage might not be representative of a large EV diffusion in the mid to long term, because of the behavior difference between early adopters and mainstream customers. Prospective studies on sustainable mobility should also try to take into account the transition towards a more sustainable mobility (more teleworking, car sharing and modal shift towards active travel modes and public transport).

Second, there is a need to develop mobility models on longer simulation time ranges than 24 hours. Indeed, weekly simulations would enable to better model the users that only occasionally connect their vehicle to the grid. Even longer simulations, on a whole year for instance, could serve to model the impact of temperature on EV electricity consumption and account for the variability of long-distance traffic during the year and different patterns of local mobility demands between working days, weekends and holidays, if enough data is available.

Third, even if spatial modeling is well studied at a distribution system level, a modeling scale that seems to be lacking in the literature is the national operator scale, with a national load curve divided into regional/smaller zone load curves. A top-down approach based on socio-economic data and/or additional local travel data could be a solution to address this gap. If enough travel survey data is available, then a bottom-up approach may prove valuable.

Fourth, studies on EV load management valuation would benefit from being integrated into global power system simulations to overcome a common assump-

⁴The main findings of this Chapter, have been accepted for publication in REI, n°178, 2022

tion in the literature that EV are price-takers on electricity markets. This point seems especially relevant for prospective long-term studies, in which EV stand to represent a significant share of the vehicle fleet.

Lastly, a final area where we believe that improvement is needed is the development of a global model of electric mobility considering as many vehicle characteristics, driver behaviors, smart charging approaches, charging point rated power and locations as possible. There is also a need to distinguish between local mobility and long-distance trips, due to their inherent constraints (such as the need for mid-trip fast-charging in the case of long-distance trips). An ambitious mobility model like this could ultimately aim to include other vehicles than plug-in electric ones, such as hydrogen or biofuel vehicles, and other mobility segments than personal cars, such as public transport or goods transport, or even disruptive new forms of mobility, in order to study how these vehicle types can share the charging infrastructure and capture the whole mobility sector to assess its interactions with the energy sector.

Bibliography

- Alonso, M., Amaris, H., Germain, J., & Galan, J. (2014). Optimal Charging Scheduling of Electric Vehicles in Smart Grids by Heuristic Algorithms. *Energies*, 7(4), 2449–2475. <https://doi.org/10.3390/en7042449>
- Amara-Ouali, Y., Goude, Y., Massart, P., Poggi, J.-M., & Yan, H. (2021). A Review of Electric Vehicle Load Open Data and Models. *Energies*, 14(8), 2233. <https://doi.org/10.3390/en14082233>
- Arias, M. B., & Bae, S. (2016). Electric vehicle charging demand forecasting model based on big data technologies. *Applied Energy*, 183, 327–339. <https://doi.org/10.1016/j.apenergy.2016.08.080>
- Ashtari, A., Bibeau, E., Shahidinejad, S., & Molinski, T. (2012). PEV Charging Profile Prediction and Analysis Based on Vehicle Usage Data. *IEEE Transactions on Smart Grid*, 3(1), 341–350. <https://doi.org/10.1109/TSG.2011.2162009>
- Balmer, M., Axhausen, K., & Nagel, K. (2006). Agent-Based Demand-Modeling Framework for Large-Scale Microsimulations. *Transportation Research Record: Journal of the Transportation Research Board*, 1985, 125–134. <https://doi.org/10.3141/1985-14>
- Beheshti, R., & Sukthankar, G. (2012). Extracting Agent-Based Models of Human Transportation Patterns. *2012 International Conference on Social Informatics*, 157–164. <https://doi.org/10.1109/SocialInformatics.2012.60>
- Black, J., Douglas, and MacDonald, & Nicholas, D. (2018). Los Angeles Air Force Base Vehicle-to-Grid Demonstration. retrieved from. <https://escholarship.org/uc/item/3f57m6g9>
- Borne, O., Perez, Y., & Petit, M. (2018). Market integration or bids granularity to enhance flexibility provision by batteries of electric vehicles. *Energy Policy*, 119, 140–148. <https://doi.org/10.1016/j.enpol.2018.04.019>
- Bowman, J., & Ben-Akiva, M. (2001). Activity-based disaggregate travel demand model system with activity schedules. *Transportation Research Part A: Policy and Practice*, 35(1), 1–28. [https://doi.org/10.1016/S0965-8564\(99\)00043-9](https://doi.org/10.1016/S0965-8564(99)00043-9)
- Chiche, A., Attard, P., Thoni, O., Nicolas, P., Novel-Cattin, F., & Scremin, L. (2017). *Les véhicules électriques au service du système électrique en 2050 ?*
- Clastres, C., Rebenaque, O., & Jochem, P. (2021). Provision of demand response by French prosumers with photovoltaic-battery systems in multiple markets. *Energy Systems*. <https://doi.org/10.1007/s12667-021-00482-4>
- Codani, P., Petit, M., & Perez, Y. (2015). Participation of an electric vehicle fleet to primary frequency control in France. *International Journal of Electric and Hybrid Vehicles*, 7(3), 233. <https://doi.org/10.1504/IJEHV.2015.071639>
- Daina, N., Sivakumar, A., & Polak, J. W. (2017). Modelling electric vehicles use: A survey on the methods. *Renewable and Sustainable Energy Reviews*, 68, 447–460. <https://doi.org/10.1016/j.rser.2016.10.005>

- Dallinger, D., Krampe, D., & Wietschel, M. (2011). Vehicle-to-Grid Regulation Reserves Based on a Dynamic Simulation of Mobility Behavior. *IEEE Transactions on Smart Grid*, 2(2), 302–313. <https://doi.org/10.1109/TSG.2011.2131692>
- Darabi, Z., & Ferdowsi, M. (2011). Aggregated Impact of Plug-in Hybrid Electric Vehicles on Electricity Demand Profile. *IEEE Transactions on Sustainable Energy*, 2(4), 501–508. <https://doi.org/10.1109/TSTE.2011.2158123>
- Domínguez-Navarro, J., Dufo-López, R., Yusta-Loyo, J., Artal-Sevil, J., & Bernal-Agustín, J. (2019). Design of an electric vehicle fast-charging station with integration of renewable energy and storage systems. *International Journal of Electrical Power & Energy Systems*, 105, 46–58. <https://doi.org/10.1016/j.ijepes.2018.08.001>
- Druitt, J., & Früh, W.-G. (2012). Simulation of demand management and grid balancing with electric vehicles. *Journal of Power Sources*, 216, 104–116. <https://doi.org/10.1016/j.jpowsour.2012.05.033>
- Eid, C., Codani, P., Perez, Y., Reneses, J., & Hakvoort, R. (2016). Managing electric flexibility from Distributed Energy Resources: A review of incentives for market design. *Renewable and Sustainable Energy Reviews*, 64, 237–247. <https://doi.org/10.1016/j.rser.2016.06.008>
- Galus, M. D., Waraich, R. A., Noembrini, F., Steurs, K., Georges, G., Boulouchos, K., Axhausen, K. W., & Andersson, G. (2012). Integrating Power Systems, Transport Systems and Vehicle Technology for Electric Mobility Impact Assessment and Efficient Control. *IEEE Transactions on Smart Grid*, 3(2), 934–949. <https://doi.org/10.1109/TSG.2012.2190628>
- Gnann, T., Stephens, T. S., Lin, Z., Plötz, P., Liu, C., & Brokate, J. (2018). *What drives the market for plug-in electric vehicles? - A review of international PEV market diffusion models*. <https://doi.org/https://doi.org/10.1016/j.rser.2018.03.055>
- Golob, T. F., & Gould, J. (1998). Projecting use of electric vehicles from household vehicle trials. *Transportation Research Part B: Methodological*, 32(7), 441–454. [https://doi.org/10.1016/S0191-2615\(98\)00001-0](https://doi.org/10.1016/S0191-2615(98)00001-0)
- Gonzalez Venegas, F., Petit, M., & Perez, Y. (2019). Can DERs fully participate in emerging local flexibility tenders? *2019 16th International Conference on the European Energy Market (EEM)*, 1–5. <https://doi.org/10.1109/EEM.2019.8916343>
- Grahn, P., Munkhammar, J., Widen, J., Alvehag, K., & Soder, L. (2013). PHEV Home-Charging Model Based on Residential Activity Patterns. *IEEE Transactions on Power Systems*, 28(3), 2507–2515. <https://doi.org/10.1109/TPWRS.2012.2230193>
- Hagman, J., Ritzén, S., Stier, J. J., & Susilo, Y. (2016). Total cost of ownership and its potential implications for battery electric vehicle diffusion. *Research in Transportation Business & Management*, 18, 11–17. <https://doi.org/10.1016/j.rtbm.2016.01.003>
- He, F., Wu, D., Yin, Y., & Guan, Y. (2013). Optimal deployment of public charging stations for plug-in hybrid electric vehicles. *Transportation Research Part B: Methodological*, 47, 87–101. <https://doi.org/10.1016/j.trb.2012.09.007>

- Hoarau, Q., & Perez, Y. (2018). Interactions between electric mobility and photovoltaic generation: A review. *Renewable and Sustainable Energy Reviews*, 94, 510–522. <https://doi.org/10.1016/j.rser.2018.06.039>
- Hodge, B.-M., Shukla, A., Huang, S., Reklaitis, G., Venkatasubramanian, V., & Pekny, J. (2011). Multi-Paradigm Modeling of the Effects of PHEV Adoption on Electric Utility Usage Levels and Emissions. *Industrial & Engineering Chemistry Research*, 50(9), 5191–5203. <https://doi.org/10.1021/ie101837w>
- Huang, S., Safiullah, H., Xiao, J., Hodge, B.-M. S., Hoffman, R., Soller, J., Jones, D., Dinger, D., Tyner, W. E., Liu, A., & Pekny, J. F. (2012). The effects of electric vehicles on residential households in the city of Indianapolis. *Energy Policy*, 49, 442–455. <https://doi.org/10.1016/j.enpol.2012.06.039>
- Iacobucci, R., McLellan, B., & Tezuka, T. (2018). Modeling shared autonomous electric vehicles: Potential for transport and power grid integration. *Energy*, 158, 148–163. <https://doi.org/10.1016/j.energy.2018.06.024>
- IEA. (2019). *Global EV Outlook 2019: Scaling-up the transition to electric mobility*. OECD. <https://doi.org/10.1787/35fb60bd-en>
- IEA. (2021). *Global EV Outlook 2021*. <https://www.iea.org/reports/global-ev-outlook-2021>
- Iqbal, M. N., Kütt, L., Lehtonen, M., Millar, R. J., Püvi, V., Rassõlkin, A., & Demidova, G. L. (2021). Travel Activity Based Stochastic Modelling of Load and Charging State of Electric Vehicles. *Sustainability*, 13(3), 1550. <https://doi.org/10.3390/su13031550>
- Jarvis, R., & Moses, P. (2019). Smart Grid Congestion Caused by Plug-in Electric Vehicle Charging. *2019 IEEE Texas Power and Energy Conference (TPEC)*, 1–5. <https://doi.org/10.1109/TPEC.2019.8662152>
- Jiang, C., Torquato, R., Salles, D., & Xu, W. (2014). Method to Assess the Power-Quality Impact of Plug-in Electric Vehicles. *IEEE Transactions on Power Delivery*, 29(2), 958–965. <https://doi.org/10.1109/TPWRD.2013.2283598>
- Kempton, W., & Tomić, J. (2005). Vehicle-to-grid power fundamentals: Calculating capacity and net revenue. *Journal of Power Sources*, 144(1), 268–279. <https://doi.org/10.1016/j.jpowsour.2004.12.025>
- Liu, S., & Etemadi, A. H. (2018). A Dynamic Stochastic Optimization for Recharging Plug-In Electric Vehicles. *IEEE Transactions on Smart Grid*, 9(5), 4154–4161. <https://doi.org/10.1109/TSG.2017.2652329>
- Lojowska, A., Kurowicka, D., Papaefthymiou, G., & van der Sluis, L. (2012). Stochastic Modeling of Power Demand Due to EVs Using Copula. *IEEE Transactions on Power Systems*, 27(4), 1960–1968. <https://doi.org/10.1109/TPWRS.2012.2192139>
- Mehta, R., Srinivasan, D., Khambadkone, A. M., Yang, J., & Trivedi, A. (2018). Smart Charging Strategies for Optimal Integration of Plug-In Electric Vehicles Within Existing Distribution System Infrastructure. *IEEE Transactions on Smart Grid*, 9(1), 299–312. <https://doi.org/10.1109/TSG.2016.2550559>
- Metais, M., Jouini, O., Perez, Y., Berrada, J., & Suomalainen, E. (2022). Too much or not enough? Planning electric vehicle charging infrastructure: A review

- of modeling options. *Renewable and Sustainable Energy Reviews*, 153, 111719. <https://doi.org/10.1016/j.rser.2021.111719>
- Mullan, J., Harries, D., Bräunl, T., & Whitely, S. (2011). Modelling the impacts of electric vehicle recharging on the Western Australian electricity supply system. *Energy Policy*, 39(7), 4349–4359. <https://doi.org/10.1016/j.enpol.2011.04.052>
- Neaimeh, M., Salisbury, S. D., Hill, G. A., Blythe, P. T., Scoffield, D. R., & Francfort, J. E. (2017). Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles. *Energy Policy*, 108, 474–486. <https://doi.org/10.1016/j.enpol.2017.06.033>
- Palmer, K., Tate, J. E., Wadud, Z., & Nellthorp, J. (2018). Total cost of ownership and market share for hybrid and electric vehicles in the UK, US and Japan. *Applied Energy*, 209, 108–119. <https://doi.org/10.1016/j.apenergy.2017.10.089>
- Pantos, M. (2012). Exploitation of Electric-Drive Vehicles in Electricity Markets. *IEEE Transactions on Power Systems*, 27(2), 682–694. <https://doi.org/10.1109/TPWRS.2011.2172005>
- Papaefthymiou, G., & Kurowicka, D. (2009). Using Copulas for Modeling Stochastic Dependence in Power System Uncertainty Analysis. *IEEE Transactions on Power Systems*, 24(1), 40–49. <https://doi.org/10.1109/TPWRS.2008.2004728>
- Pasaoglu, G., Thiel, C., Martino, A., Zubaryeva, A., Fiorello, D., Zani, L., European Commission, Joint Research Centre, Institute for Energy and Transport, & TRT Trasporti e Territorio Srl. (2013). *Projections for electric vehicle load profiles in Europe based on travel survey data*. Publications Office. Retrieved May 29, 2019, from <http://dx.publications.europa.eu/10.2790/24108>
- Plötz, P., Jakobsson, N., & Sprei, F. (2017). On the distribution of individual daily driving distances. *Transportation Research Part B: Methodological*, 101, 213–227. <https://doi.org/10.1016/j.trb.2017.04.008>
- Ramos-Real, F. J., Ramírez-Díaz, A., Marrero, G. A., & Perez, Y. (2018). Willingness to pay for electric vehicles in island regions: The case of Tenerife (Canary Islands). *Renewable and Sustainable Energy Reviews*. <https://doi.org/https://doi.org/10.1016/j.rser.2018.09.014>
- Richardson, D. B. (2013). Electric vehicles and the electric grid: A review of modeling approaches, Impacts, and renewable energy integration. *Renewable and Sustainable Energy Reviews*, 19, 247–254. <https://doi.org/10.1016/j.rser.2012.11.042>
- Rious, V., Perez, Y., & Glachant, J.-M. (2011). Power Transmission Network Investment as an Anticipation Problem. *Review of Network Economics*, 10(4). <https://doi.org/10.2202/1446-9022.1284>
- Rolink, J., & Rehtanz, C. (2013). Large-Scale Modeling of Grid-Connected Electric Vehicles. *IEEE Transactions on Power Delivery*, 28(2), 894–902. <https://doi.org/10.1109/TPWRD.2012.2236364>
- RTE. (2019). Integration of electric vehicles into the power system in France.
- Schäuble, J., Kaschub, T., Ensslen, A., Jochem, P., & Fichtner, W. (2017). Generating electric vehicle load profiles from empirical data of three EV fleets in South-

- west Germany. *Journal of Cleaner Production*, 150, 253–266. <https://doi.org/10.1016/j.jclepro.2017.02.150>
- SDES. (2008). Enquête nationale transports et déplacements (entd) 2008. <https://www.statistiques.developpement-durable.gouv.fr/enquete-nationale-transports-et-deplacements-entd-2008>
- SDES. (2019). Enquête sur la mobilité des personnes 2018-2019. <https://www.statistiques.developpement-durable.gouv.fr/enquete-sur-la-mobilite-des-personnes-2018-2019>
- Shahidinejad, S., Filizadeh, S., & Bibeau, E. (2012). Profile of Charging Load on the Grid Due to Plug-in Vehicles. *IEEE Transactions on Smart Grid*, 3(1), 135–141. <https://doi.org/10.1109/TSG.2011.2165227>
- Shen, Z.-J. M., Feng, B., Mao, C., & Ran, L. (2019). Optimization models for electric vehicle service operations: A literature review. *Transportation Research Part B: Methodological*, 128, 462–477. <https://doi.org/10.1016/j.trb.2019.08.006>
- Soares, F., Lopes, J. A., Almeida, P., Moreira, C., & Seca, L. (2011). A stochastic model to simulate electric vehicles motion and quantify the energy required from the grid. *Power Systems Computation Conference (PSCC)*.
- Spöttle, M., Jörling, K., Schimmel, M., Staats, M., Grizzel, L., Jerram, L., Drier, W., & Gartner, J. (2018). Research for TRAN Committee - Charging infrastructure for electric road vehicles, 130. [https://www.europarl.europa.eu/thinktank/en/document/IPOL_STU\(2018\)617470](https://www.europarl.europa.eu/thinktank/en/document/IPOL_STU(2018)617470)
- Steen, D., Tuan, L. A., Carlson, O., & Bertling, L. (2012). Assessment of Electric Vehicle Charging Scenarios Based on Demographical Data. *IEEE Transactions on Smart Grid*, 3(3), 1457–1468. <https://doi.org/10.1109/TSG.2012.2195687>
- Tamor, M. A., Gearhart, C., & Soto, C. (2013). A statistical approach to estimating acceptance of electric vehicles and electrification of personal transportation. *Transportation Research Part C: Emerging Technologies*, 26, 125–134. <https://doi.org/10.1016/j.trc.2012.07.007>
- Tan, J., & Wang, L. (2014). Integration of Plug-in Hybrid Electric Vehicles into Residential Distribution Grid Based on Two-Layer Intelligent Optimization. *IEEE Transactions on Smart Grid*, 5(4), 1774–1784. <https://doi.org/10.1109/TSG.2014.2313617>
- Thompson, A. W., & Perez, Y. (2019). Vehicle-to-Everything (V2X) energy services, value streams, and regulatory policy implications. *Energy Policy*, 111136. <https://doi.org/10.1016/j.enpol.2019.111136>
- UK Statistics Authority. (2018). 2018 National Travel Survey, 34. <https://www.gov.uk/government/collections/national-travel-survey-statistics>
- U.S. Department of Transportation, F. (2017). *2017 national household travel survey (nhts)*.
- Vassileva, I., & Campillo, J. (2017). Adoption barriers for electric vehicles: Experiences from early adopters in Sweden. *Energy*, 120, 632–641. <https://doi.org/10.1016/j.energy.2016.11.119>

- Weiller, C. (2011). Plug-in hybrid electric vehicle impacts on hourly electricity demand in the United States. *Energy Policy*, 39(6), 3766–3778. <https://doi.org/10.1016/j.enpol.2011.04.005>
- Wu, R. (2018). Integration of Electric Vehicles in a Flexible Electricity Demand Side Management Framework. *PhD dissertation*, 184. <http://hdl.handle.net/1842/33261>
- Yang, W., Xiang, Y., Liu, J., & Gu, C. (2018). Agent-Based Modeling for Scale Evolution of Plug-in Electric Vehicles and Charging Demand. *IEEE Transactions on Power Systems*, 33(2), 1915–1925. <https://doi.org/10.1109/TPWRS.2017.2739113>
- Yong, J. Y., Ramachandaramurthy, V. K., Tan, K. M., & Mithulananthan, N. (2015). Bi-directional electric vehicle fast charging station with novel reactive power compensation for voltage regulation. *International Journal of Electrical Power & Energy Systems*, 64, 300–310. <https://doi.org/10.1016/j.ijepes.2014.07.025>
- Yuksel, T., & Michalek, J. J. (2015). Effects of Regional Temperature on Electric Vehicle Efficiency, Range, and Emissions in the United States. *Environmental Science & Technology*, 49(6), 3974–3980. <https://doi.org/10.1021/es505621s>

2.A Recommended approaches for several EV charge fields of study

Field of study	Smart-grid, EV/DES coupling	Smart charging valuation	V2G aggregation	TSO forecasting for adequacy studies	Impacts on the distribution grid	Impacts on the transmission grid	Urban charging points sizing	Highway charging points sizing
Multiple types of vehicles studied	X			X	X	X		
Multiple charging behavior	X	X	X	X	X	X		
Multiple connection patterns (daily vs occasional vs weekend)				X	X	X		
Multiple charging location types (residential vs public vs at work)				X	X	X		
Multiple charging power	X	X		X		X	X	X
Week-long studies		X	X	X				
Local mobility	X	X	X	X	X	X	X	
Long-distance trips		X		X		X		X
Multiple journey purposes		X		X				
Distance-departure time correlation	X	X	X	X				
Spatialized models	X				X	X	X	X
MCSM approaches	X	X	X	X		X		X
MCM approaches								
ABM approaches	X				X		X	(X)

Table 2.4: Model selection guidance for studies on electric vehicles

2.B Comparison of studied articles

Study	Algorithm approach	Trip data	Connection behavior	Charging infrastructure	Smart-charging techniques
(Alonso et al., 2014)	Monte Carlo statistical	Travel survey	Systematic + Casual	Only at home	TOU, smart unidirectional and V2G
Arias & Bae, 2016)	Machine learning	Travel survey	Systematic only	Only at home	None
(Ashtari et al., 2012)	Monte Carlo statistical	Pilot project	Systematic only	Only at home	None
(Balmer et al., 2006)	Agent-based	Travel survey	Systematic only	None	None
(Beheshti & Sukthankar, 2012)	Agent-based	Travel survey	Systematic only	Only at work	None
(Black et al., 2021)	Real-life data	Pilot project	Systematic only	Only at work	V2G
(Borne, Perez, et al., 2018)	Monte Carlo statistical	Travel survey	Systematic only	Only at home	V2G
(Bowman & Ben-Akiva, 2001)	Agent-based	Travel survey	Systematic + Casual	Only at home	None
(Codani et al., 2015)	Monte Carlo statistical	Travel survey	Systematic only	Only at home	V2G
(Dallinger et al., 2011)	Monte Carlo statistical	Travel survey	Systematic only	Only at home	TOU, smart unidirectional and V2G

(Darabi & Ferdowsi, 2011)	Monte Carlo statistical	Travel survey	Systematic Casual +	Only at home	None
(Druitt & Früh, 2012)	Monte Carlo statistical	Travel survey	Systematic Casual +	Only at home	TOU, smart unidirectional and V2G
(Galus et al., 2012)	Agent-based	Travel survey	Systematic Casual +	Only at home	TOU, smart unidirectional and V2G
(Grahn et al., 2013)	Monte Carlo statistical	Travel survey	Systematic Casual +	Only at home	None
(Hodge et al., 2011)	Agent-based	Travel survey	Systematic Casual +	Only at home	TOU and smart unidirectional
(Huang et al., 2012)	Agent-based	Socioeconomic data	Systematic only	Multiple locations	TOU
(Iacobucci et al., 2018)	Agent-based	Travel survey	Systematic only	Only public charging	None
(Jarvis & Moses, 2019)	Localised Monte Carlo statistical	Averaged data	Systematic Casual +	Only at home	TOU
(Jiang et al., 2014)	Localised Monte Carlo statistical	Averaged data	Systematic Casual +	Only at home	None
(Liu & Etemadi, 2018)	Monte Carlo statistical	Travel survey	Systematic only	Only at home	Smart unidirectional
(Lojowska et al., 2012)	Monte Carlo statistical	Travel survey	Systematic Casual +	Only at home	TOU
(Mehta et al., 2018)	Monte Carlo statistical	Travel survey	Systematic only	Only at work	Smart unidirectional

(Mullan et al., 2011)	Monte Carlo statistical	Averaged data	Systematic Casual +	Only at home	Smart unidirectional
(Neaimeh et al., 2017)	Localised Monte Carlo statistical	Travel survey	Systematic only	Only at home	None
(Pantos, 2012)	Monte Carlo statistical	Averaged data	Systematic Casual +	Only at home	TOU, smart unidirectional and V2G
(Pasaoglu et al., 2013)	Monte Carlo statistical	Travel surveys	Systematic Casual +	Multiple locations	None
(Rolink & Rehtanz, 2013)	Markov chain	Travel survey	Systematic Casual +	Multiple locations	None
(Shahidinejad et al., 2012)	Monte Carlo statistical	Pilot project	Systematic Casual +	Multiple locations	None
(Soares, 2011)	Markov chain	Travel survey + pilot project	Multiple (behavioral data)	Multiple locations	None
(Steen et al., 2012)	Monte Carlo statistical	Travel survey	Systematic only	Multiple locations	Smart unidirectional
(Tan & Wang, 2014)	Monte Carlo statistical	Travel survey	Systematic Casual +	Only at home	V2G
(Weiller, 2011)	Monte Carlo statistical	Travel survey	Systematic Casual +	Multiple locations	None
(Wu, 2018)	Localised Monte Carlo statistical	Travel survey	Systematic only	Only at home	None

Table 2.5: Review of EV modeling studies

3 - Chapter 3: Electric vehicle prospective demand modeling

Summary

In order to help decarbonize the transport sector, electric vehicles (EVs) are expected to develop in the following years, and the integration of a large number of them could challenge electricity systems. This Chapter aims to develop a methodology to study the demand and connection times of EVs according to several connection behaviors of EV owners (referred to as systematic, when necessary and when convenient). Our model also generates parameters to be used as constraints to model EV smart charging. Subsequently, this framework is applied to a case study of high penetration of electric vehicles in Europe at the 2040 time horizon. Results show how much EV parameters and connection to the grid behaviors impacts the shape of EV demand curves and availability for EV demand flexibility.

3.1 Introduction

As discussed in the previous Chapters, the prospective integration of a large fleet of EVs between now and 2050 can be seen as both a challenge and an opportunity for power systems, and thus warrants further research. On one hand, simultaneous uncontrolled charging of many EVs around times of peak demand could overload the grid and reduce its capacity to match supply to total demand, or even create local grid congestion. On the other hand, EVs can also be seen as a source of demand-side flexibility that could be offered on various electricity markets and help further decarbonize the electricity generation system in addition to the transport system (Dallinger et al., 2013; Druitt & Früh, 2012; Pasaoglu et al., 2013; RTE, 2019).

EV charges could interact with several aspects of the electricity sector (Thompson & Perez, 2019): hourly dispatch and supply–demand adequacy (Druitt & Früh, 2012; Liu et al., 2014; Pantos, 2012), grid flows (at distribution scale as well as at the national scale in settings where there is non-uniform geographical distribution of EV usage and renewable energy sources) and sizing of transformers (Alonso et al., 2014; Gonzalez Venegas et al., 2019; Hodge et al., 2011), intra-day balancing markets, coupling with other distributed energy resources (Domínguez-Navarro et al., 2019; Eid et al., 2016; Hoarau & Perez, 2018), and frequency regulation (Borne et al., 2018; Codani et al., 2015). Our literature review on these research topics highlights that the topics of hourly dispatch and grid flows are mostly tackled at local scale (focusing on a small smart grid, or the distribution grid) and that the topics of short-term markets and grid frequency are usually studied in the current system but rarely to a prospective horizon (2030 and beyond). This Chapter focuses on providing a methodology to study EV patterns based on travel survey data and is

structured as follows. First, we introduce the steps of our methodology in section 3.2, before illustrating the model with prospective EV demand results for France at the 2040 time-horizon in section 3.3, then concluding and identifying the uses of our model in section 3.4.

3.2 Electric vehicle pattern modeling

This section presents the methodology selected for generating uncontrolled charge data for a large EV fleet, and the diversity of data and parameters that need to be compiled and collated in order to run the model and generate EV recharge data for multiples scenarios.

3.2.1 Selection of the EV demand modeling approach

Many mobility models have been developed over the past few years to study the development of EVs and their interaction with the transport infrastructure and the electricity supply sector, at local scale or at national scale. Daina et al. (2017) classifies these models into four main categories ('Summary travel statistics models', 'Direct use of activity travels schedules', 'Activity-based models' and 'Markov chain models'), which have been reviewed in the previous Chapter in regards to our research objectives.

In order to study the impacts of a large fleet of EVs on electricity supply–demand adequacy at national scale, results from across a whole year and at a time-resolution similar to the electricity markets studied (typically, an hourly time-resolution) are required. It also has to be possible to study various EV development and daily usage scenarios. Finally, the results need to be aggregated per class (vehicle type, charger location, connection behavior and so on). The spatial accuracy of results at local scale is a further priority.

For these reasons, we selected a methodology based on 'Direct use of activity travels schedules' but with the addition of generating random schedules from travel survey data. This provides a more representative picture of vehicle usage while enabling the study of different electric mobility growth scenarios.

Our methodology has a similar spirit to the one recently proposed by Gaete-Morales et al. (2021), which was designed to take in to account more precisely the physical characteristics of the vehicles (mass, electric motor, ancillary equipment). Due to our specific wish to address EV integration into electric dispatch simulation tools, our proposed model has less detailed representation of vehicles' physics, and a stronger focus on grid availability (demand per time window, total connected capacity per charging point type, etc.).

3.2.2 Building input data from travel survey analysis

Our model is built using data from the French 2008 National travel survey (SDES, 2008). In this dataset, 20,178 French households were surveyed and provided full

information on all their trips over a short time period (one or two days). For each trip, data available includes departure time, arrival time, distance travelled, means of transport, day of travel, purpose of journey (for instance, to get to work, go to a commercial area, pick somebody up). Additionally, notable information about the respondent's profile are also given, i.e. type of home area (city center, suburbs, rural area) and socio-professional category (student, employed, unemployed, retired). Although illustrated in this work based on French datasets, our method can be applied to other areas if such travel data is available.

For this study, we filtered the trip data in order to eliminate incomplete data and outliers and kept only trips with personal vehicles. The remaining data was then divided between "local mobility" (less than 80 kilometers away from home) and "long-distance trips". According to this definition, mobility usages with daily distances driven longer than 80 kilometers but in a single area (such as taxis, local delivery services and other professional activities involving personal vehicles) are included in the scope of what is described here as 'local mobility'.

In-depth analysis of figures from the 2008 survey revealed several characteristics of local mobility: on average, rural drivers drive longer distances, at higher speeds, leave home in the morning and get back home in the afternoon significantly earlier than those in city centers and suburbs.

In addition, we also noted a difference in trip purposes and distances driven between employees and other socio-professional categories, with most trips by employees done in the morning to get to work and in late afternoon to get back home, whereas student, unemployed and/or retired drivers to trips for various purposes that were spread much more through the day. Similar results are found by Schuller et al. (2015) using data from the German national travel survey. Finally, we found a distinction between trip data for weekdays versus Saturdays and Sundays, with fewer drivers commuting and shorter distances travelled on weekends compared to weekdays.

As a result of this analysis, we separated the travel data by type of residential area (urban, suburban, or rural), socio-professional category (employed or other) and by type of day (weekdays versus weekend day). This enabled us to study the impacts of different EV adoption and charging infrastructure development scenarios based on these data inputs.

Beyond the direct use of a travel survey dataset

The observations in this section are based on the French travel survey dataset, whose results can be slightly modified in load curves generated from our model (e.g. to modify the total distance driven per year or the share of long distance trips driven with EVs). However, it is also possible to study the effect of major changes in the nature of trips made, whether in the number of trips per vehicle, the distance traveled per trip, or a change in trip schedules. These changes may come from policy incentives, such as increasing teleworking and different urban planning, or the rise of car sharing and autonomous vehicles, among other changes. We identify three main methods for accounting for such changes in traveling habits.

First, if the changes are radical, it is possible to simply redefine the trips one wishes to model entirely. This approach seems very arbitrary, and should therefore be limited to sensitivity analysis applications.

Second, it is possible to modify an existing mobility survey in order to transcribe proposals for governmental measures, often formulated in a clear and simple way (e.g. reduce the speed by 20km/h on freeways or reduce the distance travelled by private car by 10%). This approach has the advantage of being rather easy to implement, and sticking to the proposed measures.

Third, a more comprehensive and complex approach is to use a more detailed travel model to generate a new travel dataset. Activity-based models that take into account transportation network (as presented by Axhausen and Gärling (1992), for example) can be used to study the effect of changes in urban planning. Modal choice modeling through logit models can also serve to study such mobility changes, without necessarily modeling the road network (see for example Boehm et al. (2021) for the case of freight transport).

In this manuscript, we have not applied such methods, given the very little change in the total distance travelled by private vehicle proposed by the SNBC (2019) in France (-2% between 2015 and 2050), which does not alter the results relative to our research questions.

3.2.3 Overview of the EV model developed

The approach adopted for this study is based on 5 consecutive steps, which are detailed in the following subsections: first, generation of the parameters of each EV; second, generation of the trip schedules of these EVs for the simulated time-range; third, computation of the evolution of each vehicle's location and consumption throughout the simulation; fourth, simulation of the connection of EVs to the grid and the subsequent uncontrolled electricity demand; and fifth, aggregation of the results for every simulated EV into groups of results. This methodological framework is depicted in Figure 3.1.

As vehicle and trip parameters are randomly generated, a large number of EVs need to be simulated (at least 10,000 vehicles) in order to achieve robust statistical significance, following the principles of Monte-Carlo simulation.

The following sections present the analysis of travel survey data to generate trip input data for the model, and the 5 steps in our methodology.

3.2.4 Generation of vehicle parameters

The first step in our EV charge modeling approach is to generate the technical parameters of the EVs in the simulation. For each vehicle, we used input data and assumptions to randomly generate their type (BEV, PHEV, FCEV), battery capacity, charging behavior (detailed in section 3.2.7), residential area, socio-professional category, and charging points available (only at home, only at work, only at public charging stations, or a combination of these). The distributions of the previously-

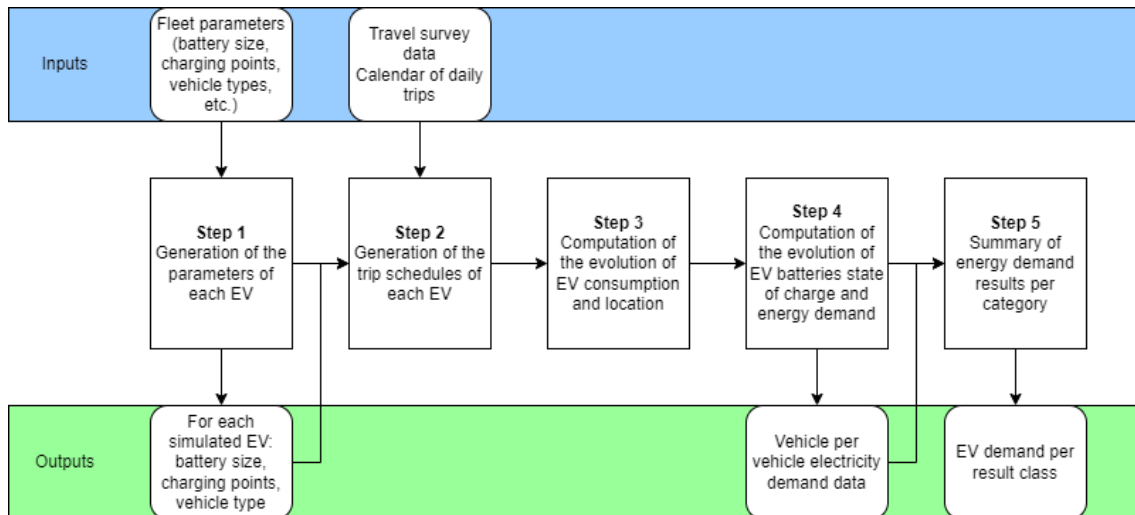


Figure 3.1: Global framework of the proposed methodology

described parameters serve as inputs to this vehicle generation process to ensure that the vehicle fleet generated is statistically representative of the estimated national fleet. All these parameters are not generated independently from each other, as PHEVs for instance tend to have a shorter electric drive range than BEVs, and most charging points at a workplace are only available to employees. Plötz et al. (2018) show empirically how much annual distances driven differ from a PHEV model to another, but in this work, we consider that PHEV battery capacity is not correlated to the distances driven with the vehicle.

3.2.5 Trip schedule generation

Once the vehicle parameters are set, the second step consists in generating the travel schedule of the vehicles throughout the simulation. For each vehicle and for every day of the simulation (typically 365 days), we randomly draw from travel data a set of trip parameters corresponding to type of day, type of home area and socio-professional category of the EV owner. The trip departure times and distances of these trips are drawn together as a set of trips from travel survey data in order to take into account the correlation between these parameters. A percentage of the vehicles are not used every day, in line with data from the travel survey data, so there is a probability of no trips assigned in addition to travel-survey trips.

One way to generate a greater diversity of travel patterns is to add white noise to the travel survey data (for instance $\pm 10\%$ on distances and ± 30 min on departure times), but this was found to have negligible effect on EV demand results with the data used here, as the number of respondents is high enough for good statistical representativeness. However, as not enough data is available on the weekly driving patterns of EV drivers, the days of travel are drawn independently for every given EV (keeping the structure of week composed of 5 working days, Saturdays

and Sundays, drawing trips accordingly). This approximation does not appear to have a significant impact on charging results aggregated at national scale.

3.2.6 Vehicle consumption and location modeling

The third step of our methodology is to compute the evolution of EV battery discharge for mobility use and location for each vehicle, at a time-step length chosen as an input of the model. Depending on the study (hourly electricity markets, short-term markets), the time-step could range from one hour to a few minutes. The values for EV consumption and location are derived directly from the travel schedules and consumption of the vehicles (see equation 3.1). EV consumption varies as function of several factors, including driving speed, outdoor temperature and use of ancillary equipment (Iora & Tribioli, 2019; Yuksel & Michalek, 2015). To simplify, we only take into account the impacts of temperature and driving speed in the model.

$$Consumption_{ev,n}(t) = distancedriven_{ev,n}(t) * consumption_{perkm}(temperature(t), speed_{ev,n}(t)) \quad (3.1)$$

where:

$Consumption_{ev,n}(t)$ is the consumption on the road of EV n at time step t (kW)

$distancedriven_{ev,n}(t)$ is the distance driven by EV n at time step t (km)

$consumption_{perkm}$ is the energy consumption per km (kW/km)

$temperature(t)$ is the temperature at time step t (national average) (°C)

$speed_{ev,n}(t)$ is the average driving speed of EV n at time step t (km/h)

After the location and consumption of vehicles has been computed, step four involves modeling EV owner behavior in terms of connection to the grid. As stated above, our model is able to study several vehicle types interacting with the electricity system, namely BEVs, PHEVs and FCEVs.

For BEVs, we consider total driving range by not assigning local daily mobility distances longer than their drive range (indeed, EV users that drive very long daily distances will not buy an EV with lower driving range than these distances). As a result, the vehicle battery is sufficient to cover their travel schedule in the simulation.

If the vehicle is a PHEV, we assume here that its usage in terms of mobility patterns will be similar to a combustion-engine vehicle. We also consider that PHEV owners maximize the share of their distances driven in electric mode, even though ex-post analysis of 100,000 PHEVs from Plötz et al. (2020) suggested that PHEVs are not currently used this way. However, this assumption is justified here by assuming that in the long-term, PHEV users will be incentivized to minimize their combustion-engine usage in an effort to cut their transport-related carbon footprint. Additionally, when studying the electrical system, this assumption is the PHEV usage that maximizes total EV demand, which is what the electrical system needs to accommodate.

Finally, FCEVs are modelled is much the same way as PHEVs but without the possibility to plug into the power grid, which means that in our simulation we only compute their total hydrogen demand.

3.2.7 Grid connection and uncontrolled charge modeling

Several papers (Enedis, 2020; Gonzalez Venegas et al., 2019; Soares et al., 2011) have shown the diversity of EV owner behaviors: some connect their vehicle daily, while others only connect it when the state of charge is low. This is largely dictated by access to a charging point, with a share of EV owners possessing a charging point at home while others rely on the public charging infrastructure. As a result, we introduced three connection-to-grid behaviors, summed up in Figure 3.2.

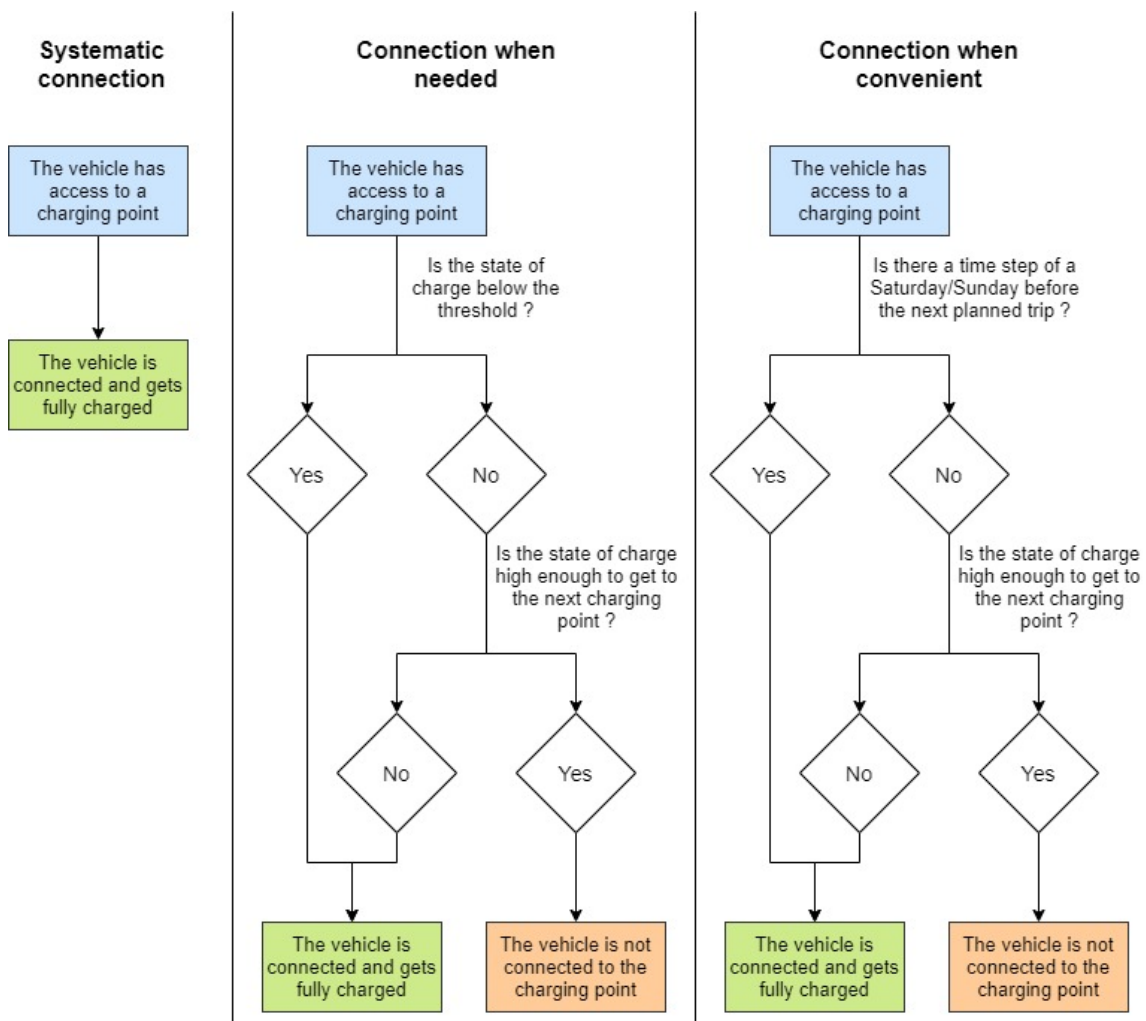


Figure 3.2: Flowchart of the three connection-to-the-grid behaviors studied

First, the systematic connection behavior, in which the vehicle is connected every time it is parked, and a charging point is available.

Second, the connection when needed behavior, defined as follows: the EV owner only connects their vehicle to the grid if a charging point is available and its state of charge is below a threshold SOC_{min} , defined either as a distance that the vehicle can drive before the battery is depleted (typically 50km) or a percentage of its remaining battery charge (typically 30%).

Furthermore, every time the vehicle gets to a charging point, it also connects if the remaining state of charge is not enough to drive in electric mode until the next charging point on its route schedule. This condition ensures that BEVs can match their trip schedule and that PHEVs can maximize their electricity-powered distances.

Third, the connection when convenient behavior, in which EVs are only connected to the grid on weekends (randomly drawn between Friday evening, Saturday or Sunday), as the behavioral studies cited above show that a significant share of EV owners report connecting their vehicle once a week and when convenient. Similarly to 'connection when needed', we ensure that EVs are also plugged into the grid if they cannot reach the next charging point in electric mode.

3.2.8 Long-distance trips

In the analysis of travel survey data, we separated local mobility data from long-distance trips, described in the French travel survey (SDES, 2008) as trips further than 80 km from home. Long-distance trips thus differ from other shorter trips by their inherent characteristics. A long-distance trip may exceed the drive range of some BEVs and most PHEVs in electric mode. However, fast chargers are developing along main road corridors in order to facilitate EV development (Funke et al., 2019; Neaimeh et al., 2017).

Thus, in our model, BEVs are able to connect and charge in the middle of a long-distance trip. The three charging behaviors introduced in the previous part share the same behavior during a long-distance trip: if the state of charge of the battery drops below a threshold $SOC_{min, long\ distance}$ (typically $15 \pm 5\%$), then the BEV stops and recharges to $SOC_{max, long\ distance}$. $SOC_{min, long\ distance}$ considers both the availability of fast chargers (as an assumption as no spatial modelling and geographic location of chargers are considered here) and the behavior of drivers that anticipate the mid-trip charge to avoid fully depleting their battery. $SOC_{max, long\ distance}$ stands for the point when the charging speed of the battery decreases, approximately 90%, as measured by Mies et al. (2018).

We consider that due to the high cost and waiting time of highway fast-chargers, PHEVs will not recharge their electric battery during a long-distance trip.

The share of long-distance trips among all trips, i.e. 20% of distances travelled in the French national travel survey data, implies that the amount of long-distance trips each day within the EV charging model may not be large enough to yield good statistical significance of this specific trip category, especially in mid-trip fast-charging results and the distribution of trips through the year. To overcome this

limitation, we can either substantially increase the number of vehicles in the simulation (at a cost of much longer computational times) or, as a preferred solution, generate mid-trip charging patterns of EVs at fast-chargers (in which every vehicle is assigned to long-distance trips) in another simulation before incorporating these results into the earlier simulations.

3.3 Case study: EV uncontrolled demand and connection to the grid data in France at the year-2040 time horizon

3.3.1 Data and assumptions

For our case study, we selected a prospective analysis of the integration EVs in the European electricity system in 2040. This time horizon corresponds to a turning point for the transportation sector, as several European countries and cities have planned to ban the sales of new thermal vehicles by then. Our focus will be made on the vehicle demand in France, based on the travel data sets of the French travel surveys.

Vehicle parameters

Based on the most ambitious EV development scenarios from RTE (2019) and SNBC (2019), the selected parameters for the vehicles in our case study are gathered in Table 3.1. EV represent around two thirds of all personal vehicles in France by this time horizon. The battery capacities are expected to increase in the coming years, in order to overcome the EV development barrier of drivable range.

Number of thermal vehicles in France	12.1 Million
Number of electric vehicles in France	24.4 Million
BEV share in the vehicle stock	85%
PHEV share in the vehicle stock	15%
FCEV share in the vehicle stock	0%
Battery capacity of BEVs (mean value)	78 kWh
Standard deviation of BEV battery capacity	16 kWh
Battery capacity of PHEVs (mean value)	15.6 kWh
Standard deviation of PHEV battery capacity	3 kWh

Table 3.1: Vehicle parameters in the selected scenario, at the 2040 time horizon, data adapted from RTE (2019)

Charging infrastructure available

Regarding the charging stations available, we selected results from RTE (2019) at the 2040 time horizon. The power repartition and availability of those charging points are detailed in Tables 3.2 and 3.3. This repartition implies that, in this study, a great share of EV demand occurs at or around the household location, compared to the recharge at work and at other places. We also consider that every EV is able to be charged at every charging point (no incompatibilities across EV brands as observed nowadays). The charging infrastructure on highways is not limited in our case study, in order to compute an upper bound of EV demand on highways, even if some chargers may not be used every day of the year and thus not be profitable (which is a topic out of or scope of analysis).

	3.7 kW	7.4 kW	22 kW	50 kW	130 kW	350 kW
Charging points at or around home	30%	70 %	0%	0%	0%	0%
Charging points at work	7%	60%	26%	7%	0%	0%
Charging points at public locations	0%	27%	13%	53%	7%	0%
Charging points on highways	0%	0%	0%	17%	47%	36%

Table 3.2: Charging power breakdown per location, data adapted from RTE (2019)

	Employees	Professional vehicle	Others (students, unemployed, retired)
Only at home	49%	35%	88%
Only at work	15%	53%	0%
Only at public locations	1%	0%	0%
At home and at work	22%	0%	0%
At home and at public locations	4%	4%	12%
At work and at public locations	4%	4%	0%
Both at home, at work and at public locations	5%	4%	0%

Table 3.3: Availability of charging points and usage per EV owner profile, data adapted from RTE (2019)

3.3.2 Prospective EV demand curves

In this section are presented the results of uncontrolled EV charge, from the model described in section 3.2. All those results are based on data from the French National travel survey (SDES, 2008).

According to this travel survey, and considering that electric mobility diffusion is faster for vehicle users that drive the longer distances per year (as shown by Plötz et al. (2020) for PHEVs), we estimate that the average BEV is driven on average 13,908 kilometers per year (11,241 km from local trips and 2,667 from long distance trips), while the average PHEV is driven on average 14,970 kilometers per year (11,241 km from local trips and 3,729 from long distance trips). From the travel survey data, and our assumptions on EV consumption as a function of temperature, the computed average consumption for local trips is 0,141 kWh/km, while, due to higher speeds on long distance trips, the computed average consumption for those is 0,234 kWh/km. On average, the total yearly energy demand per BEV reaches 2.21 MWh, while total yearly demand per PHEV reaches 2.46 MWh. Secondly, the share of PHEV energy consumption in thermal mode from our results is only 10.5%, as PHEVs are assumed to maximize their usage of electricity for their trips, compared to around 63% from current empirical data, worldwide (Plötz et al., 2020), especially because of company cars. This share of distances driven in thermal mode could evolve, because of new regulations and increasing fossil fuel prices. As a result, the total electricity demand from the 24.4 Million electric vehicles reaches 53.9 TWh in 2040, which represents around 12% of current total electricity consumption in France.

EV demand per area

In Figure 3.3, we compare the power demand from EVs at different areas that have been selected from the travel survey. During working days, uncontrolled peak demand occurs later in the evening in the major cities, than in other urban areas, and even more than in rural areas. However, vehicle users from rural areas travel greater distances per day during the week and a higher speed, so the weekly consumption per EV is 28% higher in rural than urban areas (35 kWh per week on average for major cities dwellers, 37.4 kWh for other urban dwellers and 48.1 kWh for rural dwellers). This result implies that, for a given amount of EVs in the fleet, the diffusion in the society of those vehicles has a notable effect on the total electricity demand of the transport sector. For the rest of our case study, we assume that the spatial distribution of EVs among areas (rural, urban and major cities) in 2040 is similar to the current distribution of all individual vehicles.

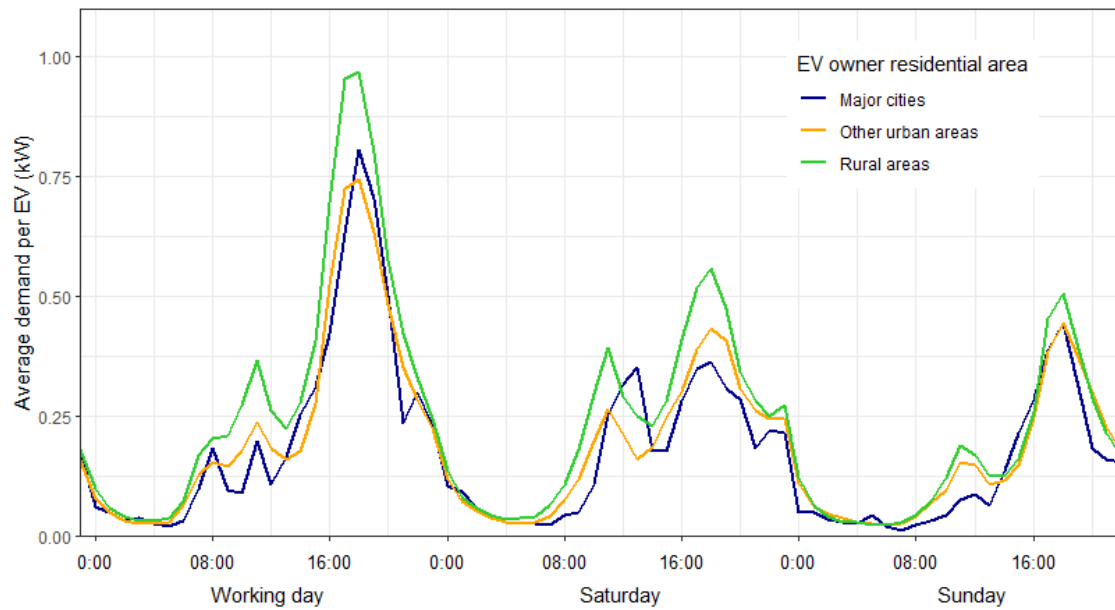


Figure 3.3: Uncontrolled EV demand for different residence location of EV owner, every vehicle follows the systematic connection behavior

Demand per charging point location

Then in Figure 3.4, we show the results in terms of charging location. During working days, charging at work occurs mainly in morning and early afternoon hours (from around 08:00am to 01:00pm), while charging at home is more spread during the day, with a peak from 07:00pm to 10:00pm). Public charging is spread out more evenly throughout the day, even though it only stands for a small share of EV charge. During Saturdays and Sundays, the total and peak energy demand are lower than on working days, under "systematic" and "connection when needed" behaviors, as less vehicles are driving on these days. Moreover, the share of vehicle owners going to work on weekends is rather low compared to working days, and so is the demand from chargers at work.

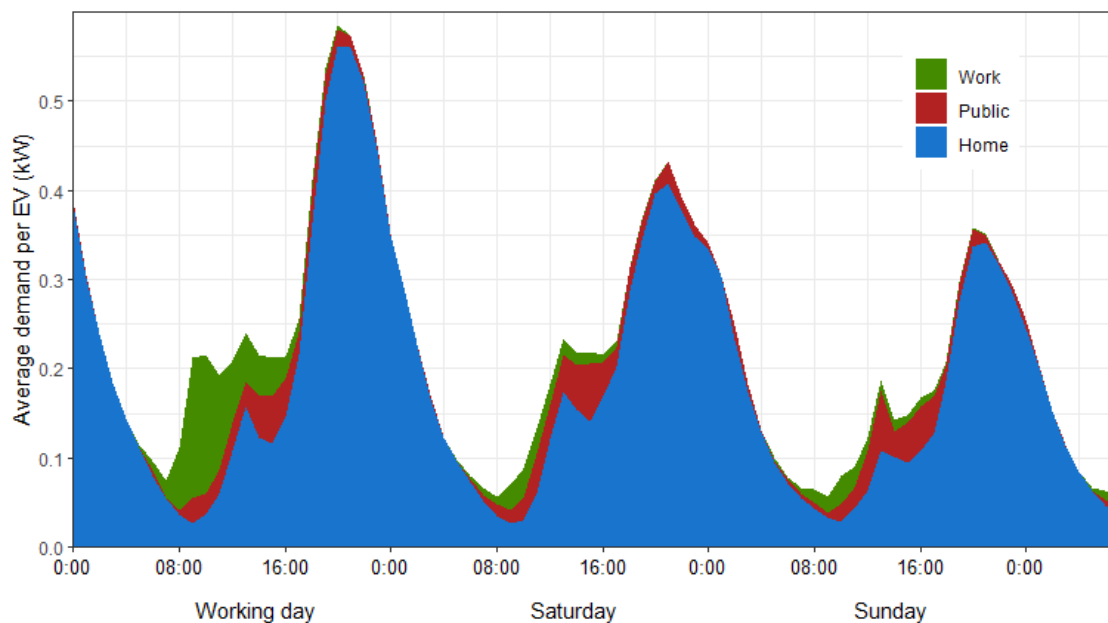


Figure 3.4: Uncontrolled charging demand separated by charging location, with a repartition of 40% "systematic" behavior and 60% "connection when needed" behavior

Demand for the charging behaviors studied

Finally, we compare charging behavior of EV owners, as described in section 3.2.7, namely the systematic connection, connection when necessary and connection when convenient behaviors. We selected 50% and 5% as two variations for the state of charge limit of the connection when necessary behavior. The 50% state of charge variation stands for EV owners that anticipate the charge of their vehicles, while the 5% state of charge variation means that the vehicle are connected as little as possible to match their mobility needs. In addition, we can note that the connection behavior in which EV users charge their vehicle when the state of charge gets below 50% should provide results similar to a last minute connection behavior, but with EVs with smaller batteries.

Fast chargers could also emerge in urban areas as an option for EV charge of vehicle owners that do not own a private parking spot. Funke et al. (2019) show that the development of a fast charging infrastructure could turn out less costly for the society than an increase in battery capacity, in order to overcome the driving range barrier for EV development. Indeed, we also simulated a connection when necessary behavior in which EVs are connected to fast chargers (130 kW) when their state of charge is not sufficient for the trips of the following day, which replicates the refueling of thermal vehicles.

Figure 3.5 illustrates the share of BEVs connected to the grid per behavior studied. We identify that at night, around 90% of BEVs in "systematic" connection

mode have access to a charging point in our scenario. Moreover, only around 5% of BEVs in connection "when needed" (with the connection threshold at the state of charge of 5% of battery capacity) are connected each day, which means that on average, with 76 kWh batteries, BEVs need to connect less than once a week. Additionally, we identify that EV users in the connection when convenient mode connect mainly on Friday evening, and throughout the weekend. As a result, if a significant share of EV users tend to connect on weekends, peak demand of 2.5 kW per EV are to be expected on Fridays and Saturdays in the evenings.

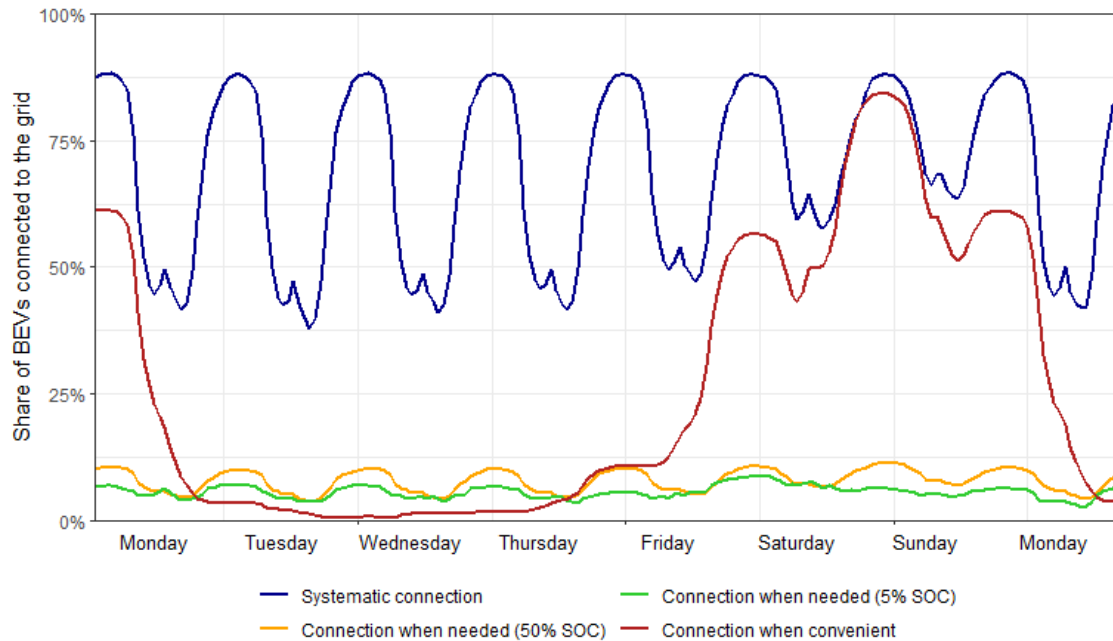


Figure 3.5: Evolution of the share of BEVs connected to the grid during the week

We also compare BEV and PHEV connection behaviors in Figures 3.6 and 3.7. First, for BEVs, it appears that the shape of the demand curve differs a lot from a connection behavior to another. For the "systematic" connection and the connection "when needed" with fast chargers, most vehicles are fully charged in less than an hour, which means that demand of a large share of BEVs is synchronized right after peak trip times (around 08:00am, at mid-day and mostly between 05:00pm and 09:00pm, when most vehicles are driven back home). The connection behavior using fast chargers is, as expected, the behavior with the highest peak demand (0.85 kW per vehicle, at 07:00pm), but notably, the shape of the load curve and peak demand appear to be quite similar to systematic connection of BEVs at much lesser charging powers. The demand of the connection "when needed" behavior at regular charging power (3.7 kW or 7.4 kW) is much more spread through the night, as the full charge of vehicles takes several hours for BEVs with large batteries. On the other hand, for PHEVs, we see little difference between charging behaviors in Figure 3.7, with most vehicles finishing their charge before 11:00pm in the evening, because of smaller batteries. This result shows that as PHEVs are

assumed to maximize the share of their distance travelled in electric mode, they are being connected nearly every day in this model. Even if an averaged week day is illustrated in Figures 3.6 and 3.7, no significant differences are observed between each working day. The main difference being the lower consumption on weekends, as illustrated in the previous Figures 3.3 and 3.4.

On average, in order to match their mobility needs, EVs need to be connected 35 minutes per day. Figure 3.8 illustrates for each behavior studied the amount of time that EVs spend connected to the grid while not charging. It appears that EVs connected to a charging point on a "systematic" basis spend 25 more time than needed connected to the grid (these vehicles being "not connected" a share of the time, when they are driven or away from an accessible charging point). As a result, these vehicles offer a great window of opportunity for smart charging by delaying the beginning of their charging session. However, other connection patterns only show limited potential for the delay of the charge of batteries, as connecting an EV only "when needed" means that the vehicle stays connected 2 or 3 times more than necessary on average. Were these vehicles smartly charged, we could avoid charging them during peak load, but we could not shift the whole charging session during the lowest electricity price hour as the process takes several hours. The only exception to that statement being the connection when convenient behavior on week-ends, in which the window for delaying the charge of the vehicle appears similar to the systematic connection behavior.

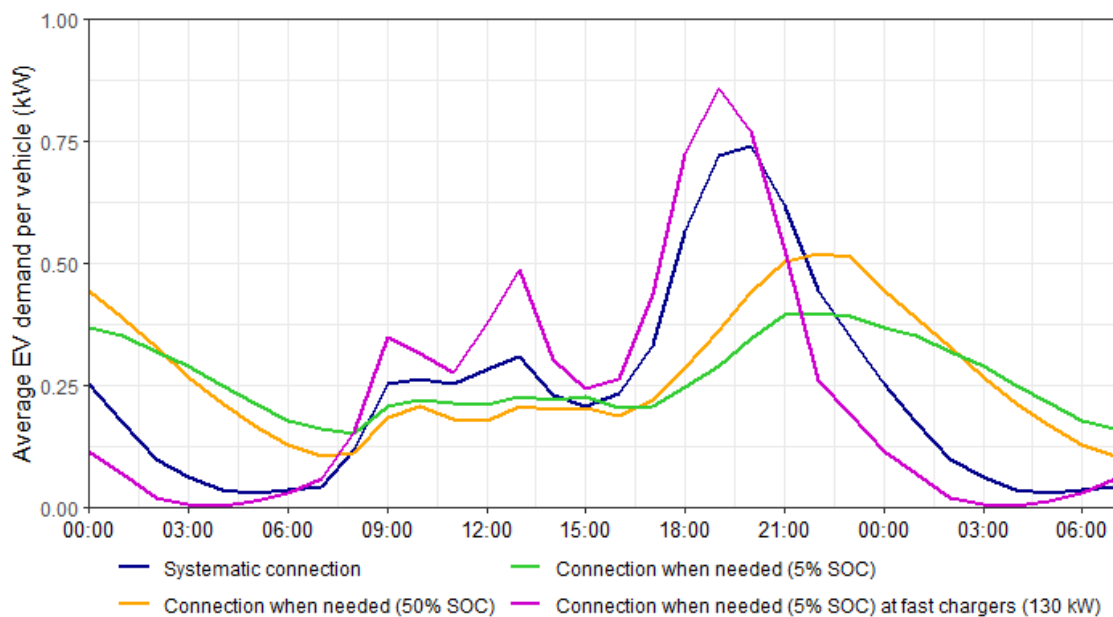


Figure 3.6: BEV demand curve on the average week day, for various connection behaviors

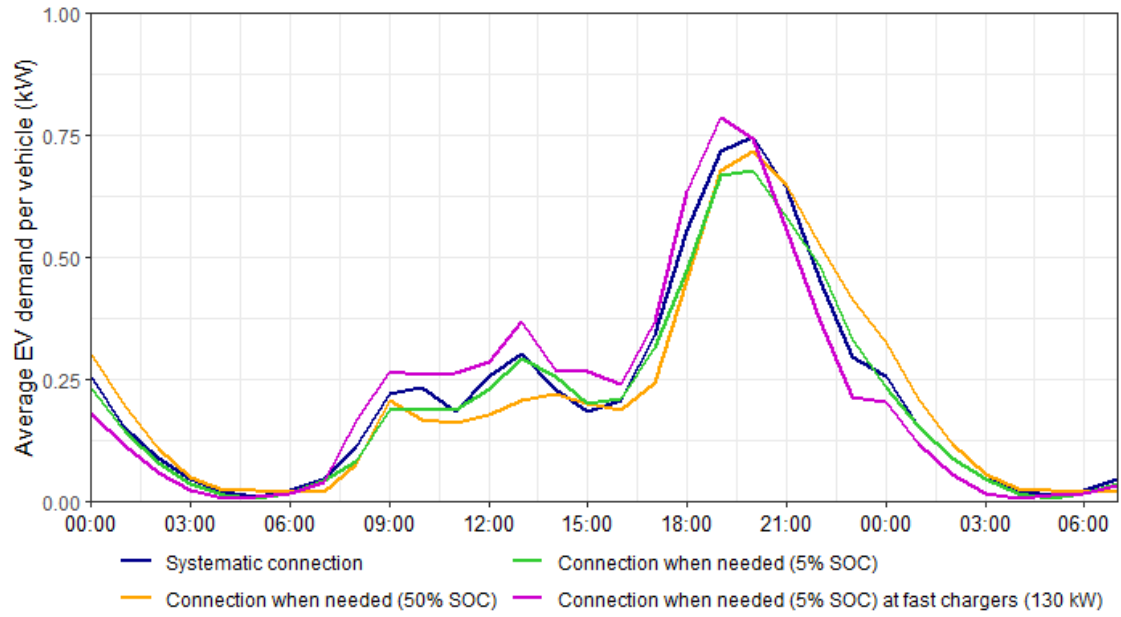


Figure 3.7: PHEV demand curve on the average week day, for various connection behaviors

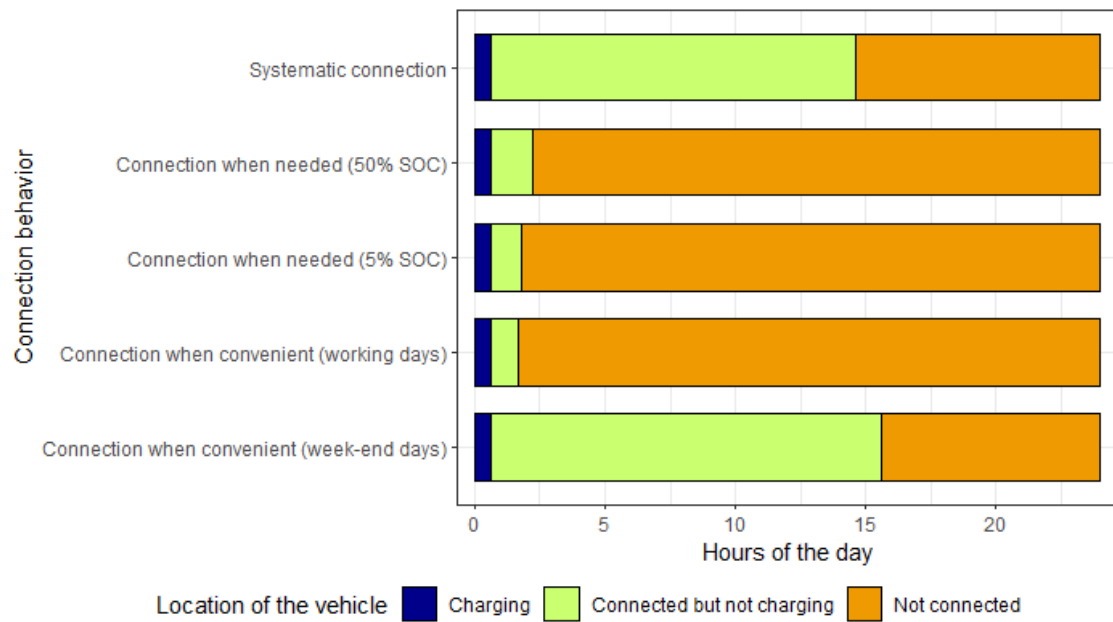


Figure 3.8: Repartition of time connected to the grid per behavior studied

The case of long distance trips

There is still some uncertainty on how EVs will be used for long distance trips. On the one hand, Jakobsson et al. (2016) show that EVs are more suited to households that own at least two cars, which would not use their EV for long distance trips. On the other hand, in the medium term, scenarios with widespread EV adoption (around two thirds of all individual vehicles in our scenario) imply that a significant share of households would only have access to an EV for their long distance car journeys.

In order to incorporate these observations in our case study, we assumed that PHEVs are used as much as thermal vehicles but never charge their battery mid-trip, BEVs below 50 kWh are not used for long distance trips, and 50% of BEVs above 50kWh are used for long distance trips, given that 35% of households own several vehicles in France, as indicated by INSEE (2017b).

Additionally, the major parameter to study EV long distance related demand is proper data about the repartition of those long distance trips during the year, which national travel surveys are usually not built to provide. As a result, we estimated the amount of long distance trips each day from another study, which relates the share of people away from their home each day (INSEE, 2017a). Results on the long distance related EV demand through the year can be found in Figure 3.9. We highlight that long distance trips are concentrated in peaks at the weekly (more trips on weekends) and annual scale, as found in Plötz et al. (2017). The highest peak demand days are found at Summer holidays and around Christmas, with smaller peaks in Spring.

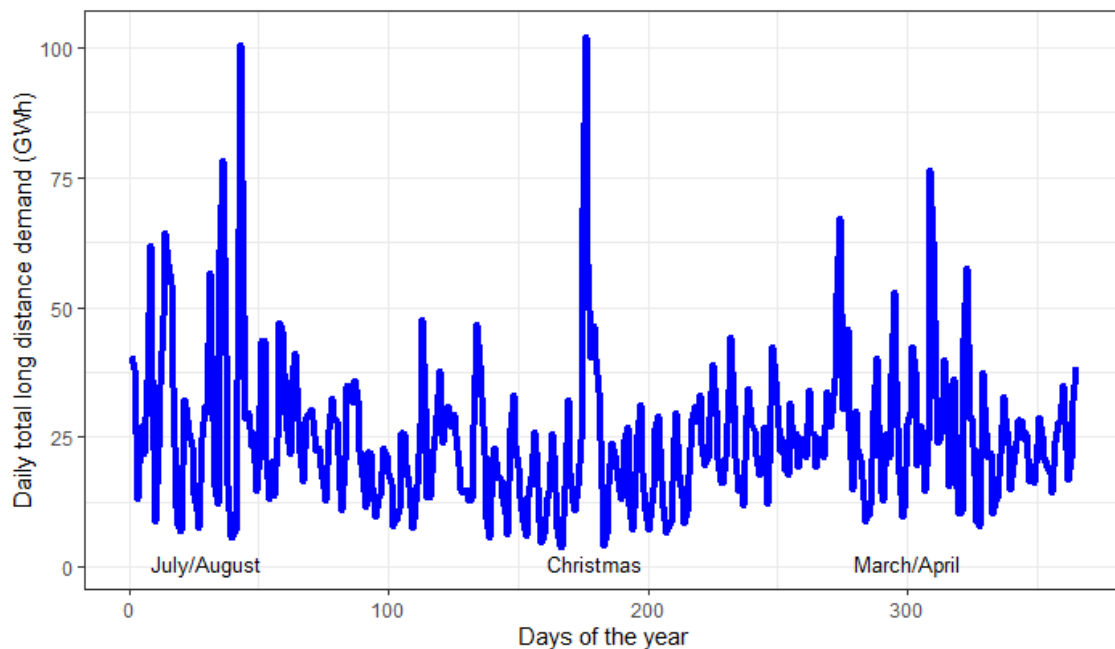


Figure 3.9: EV long distance demand through the year (from July 1st to June 31st for better readability of the Christmas peak)

3.4 Discussion and conclusion

EVs are set to develop in the following years, and could possibly reach a large market share of the transport sector by 2050. In this Chapter, we reviewed the estimated demand curves and availability at charging stations of one of the most ambitious EV development scenarios in France, to the extent of 53.9 TWh in 2040, for the charge of 24.4 Million electric vehicles, which is around 8% of total projected electricity demand in France by that time.

In order to analyze the effects of EV diffusion on power systems, we propose in this Chapter a methodology to generate travel patterns and EV connection and demand data from travel survey data and assumptions on EV characteristics. This methodology enables the study of a large diversity of vehicles (BEVs, PHEVs, FCEVs, from different segments), vehicle ownership (rather employees commuting to work, company-owned or other), vehicle usage (local mobility and long distance trips), charging stations available (at various locations and rated power) and connection behaviors (systematic or less frequent).

Ideally, the results presented here would be validated by empirical data, derived from real world EV demand measurements. Unfortunately, no such open source high quality individual EV charging data is currently available. And even if such data were available, there might not be representative on EV usage at the 2040 time horizon. However, the load curves obtained through our model do not seem too dissimilar from the results of other studies of the literature referenced in this Chapter.

Our case study highlights that the profile of EV adopters among the population (urban or rural dwellers; employees or other socio-economic classes) has an impact on EV demand times and total energy consumption. EV demand is 28% higher in rural areas (compared to urban), and employees trips are more homogeneous than others, which implies higher uncontrolled peak demand at 18:00-19:00 if EVs are mainly used for commuting to work.

The low usage rate of public chargers also questions the profitability of such chargers without public funding.

Finally, our analysis suggests that the connection behavior of EV users, from daily connection to connection only when necessary is a key factor of smart charging potential and peak demand mitigation. Incentivizing EV owners that are willing to provide flexibility to connect their vehicle as much as possible would be necessary for maximizing the flexibility provided.

This analysis only enables the study of uncontrolled vehicles and relies on the methodology presented on the next Chapter to study the smart charging modes of EVs, using the connection to the grid data computed in this Chapter.

Bibliography

- Alonso, M., Amaris, H., Germain, J., & Galan, J. (2014). Optimal Charging Scheduling of Electric Vehicles in Smart Grids by Heuristic Algorithms. *Energies*, 7(4), 2449–2475. <https://doi.org/10.3390/en7042449>
- Axhausen, K. W., & Gärling, T. (1992). Activity-based approaches to travel analysis: Conceptual frameworks, models, and research problems. *Transport Reviews*, 12(4), 323–341. <https://doi.org/10.1080/01441649208716826>
- Boehm, M., Arnz, M., & Winter, J. (2021). The potential of high-speed rail freight in Europe: How is a modal shift from road to rail possible for low-density high value cargo? *European Transport Research Review*, 13(1), 4. <https://doi.org/10.1186/s12544-020-00453-3>
- Borne, O., Perez, Y., & Petit, M. (2018). Market integration or bids granularity to enhance flexibility provision by batteries of electric vehicles. *Energy Policy*, 119, 140–148. <https://doi.org/10.1016/j.enpol.2018.04.019>
- Codani, P., Petit, M., & Perez, Y. (2015). Participation of an electric vehicle fleet to primary frequency control in France. *International Journal of Electric and Hybrid Vehicles*, 7(3), 233. <https://doi.org/10.1504/IJEHV.2015.071639>
- Daina, N., Sivakumar, A., & Polak, J. W. (2017). Modelling electric vehicles use: A survey on the methods. *Renewable and Sustainable Energy Reviews*, 68, 447–460. <https://doi.org/10.1016/j.rser.2016.10.005>
- Dallinger, D., Gerda, S., & Wietschel, M. (2013). Integration of intermittent renewable power supply using grid-connected vehicles – A 2030 case study for California and Germany. *Applied Energy*, 104, 666–682. <https://doi.org/10.1016/j.apenergy.2012.10.065>
- Domínguez-Navarro, J., Dufo-López, R., Yusta-Loyo, J., Artal-Sevil, J., & Bernal-Agustín, J. (2019). Design of an electric vehicle fast-charging station with integration of renewable energy and storage systems. *International Journal of Electrical Power & Energy Systems*, 105, 46–58. <https://doi.org/10.1016/j.ijepes.2018.08.001>
- Druitt, J., & Früh, W.-G. (2012). Simulation of demand management and grid balancing with electric vehicles. *Journal of Power Sources*, 216, 104–116. <https://doi.org/10.1016/j.jpowsour.2012.05.033>
- Eid, C., Codani, P., Perez, Y., Reneses, J., & Hakvoort, R. (2016). Managing electric flexibility from Distributed Energy Resources: A review of incentives for market design. *Renewable and Sustainable Energy Reviews*, 64, 237–247. <https://doi.org/10.1016/j.rser.2016.06.008>
- Enedis. (2020). Enquête comportementale auprès des possesseurs de véhicules électriques : Habitudes de roulage et de recharge.
- Funke, S. Á., Plötz, P., & Wietschel, M. (2019). Invest in fast-charging infrastructure or in longer battery ranges? A cost-efficiency comparison for Germany. *Applied Energy*, 235, 888–899. <https://doi.org/10.1016/j.apenergy.2018.10.134>

- Gaete-Morales, C., Kramer, H., Schill, W.-P., & Zerrahn, A. (2021). An open tool for creating battery-electric vehicle time series from empirical data, *emobpy*. *Scientific Data*, 8(1), 152. <https://doi.org/10.1038/s41597-021-00932-9>
- Gonzalez Venegas, F., Petit, M., & Perez, Y. (2019). Can DERs fully participate in emerging local flexibility tenders? *2019 16th International Conference on the European Energy Market (EEM)*, 1–5. <https://doi.org/10.1109/EEM.2019.8916343>
- Hoarau, Q., & Perez, Y. (2018). Interactions between electric mobility and photovoltaic generation: A review. *Renewable and Sustainable Energy Reviews*, 94, 510–522. <https://doi.org/10.1016/j.rser.2018.06.039>
- Hodge, B.-M., Shukla, A., Huang, S., Reklaitis, G., Venkatasubramanian, V., & Pekny, J. (2011). Multi-Paradigm Modeling of the Effects of PHEV Adoption on Electric Utility Usage Levels and Emissions. *Industrial & Engineering Chemistry Research*, 50(9), 5191–5203. <https://doi.org/10.1021/ie101837w>
- INSEE. (2017a). Séjours touristiques des français, 1. <https://www.insee.fr/fr/statistiques/3202047>
- INSEE. (2017b). Tableaux de l'économie française, budget des ménages, 1. <https://www.insee.fr/fr/statistiques/4764315>
- Iora, P., & Tribioli, L. (2019). Effect of Ambient Temperature on Electric Vehicles' Energy Consumption and Range: Model Definition and Sensitivity Analysis Based on Nissan Leaf Data. *World Electric Vehicle Journal*, 10(1), 2. <https://doi.org/10.3390/wevj10010002>
- Jakobsson, N., Gnann, T., Plötz, P., Sprei, F., & Karlsson, S. (2016). Are multi-car households better suited for battery electric vehicles? – Driving patterns and economics in Sweden and Germany. *Transportation Research Part C: Emerging Technologies*, 65, 1–15. <https://doi.org/10.1016/j.trc.2016.01.018>
- Liu, Z., Wu, Q., Nielsen, A., & Wang, Y. (2014). Day-Ahead Energy Planning with 100% Electric Vehicle Penetration in the Nordic Region by 2050. *Energies*, 7(3), 1733–1749. <https://doi.org/10.3390/en7031733>
- Mies, J., Helmus, J., & van den Hoed, R. (2018). Estimating the Charging Profile of Individual Charge Sessions of Electric Vehicles in The Netherlands. *World Electric Vehicle Journal*, 9(2), 17. <https://doi.org/10.3390/wevj9020017>
- Neaimeh, M., Salisbury, S. D., Hill, G. A., Blythe, P. T., Scoffield, D. R., & Francfort, J. E. (2017). Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles. *Energy Policy*, 108, 474–486. <https://doi.org/10.1016/j.enpol.2017.06.033>
- Pantos, M. (2012). Exploitation of Electric-Drive Vehicles in Electricity Markets. *IEEE Transactions on Power Systems*, 27(2), 682–694. <https://doi.org/10.1109/TPWRS.2011.2172005>
- Pasaoglu, G., Thiel, C., Martino, A., Zubaryeva, A., Fiorello, D., Zani, L., European Commission, Joint Research Centre, Institute for Energy and Transport, & TRT Trasporti e Territorio Srl. (2013). *Projections for electric vehicle load profiles in Europe based on travel survey data*. Publications Office. Retrieved May 29, 2019, from <http://dx.publications.europa.eu/10.2790/24108>

- Plötz, P., Funke, S. Á., & Jochem, P. (2018). Empirical Fuel Consumption and CO₂ Emissions of Plug-In Hybrid Electric Vehicles: Fuel Consumption of Plug-In Hybrid Electric Vehicles. *Journal of Industrial Ecology*, 22(4), 773–784. <https://doi.org/10.1111/jiec.12623>
- Plötz, P., Jakobsson, N., & Sprei, F. (2017). On the distribution of individual daily driving distances. *Transportation Research Part B: Methodological*, 101, 213–227. <https://doi.org/10.1016/j.trb.2017.04.008>
- Plötz, P., Moll, C., Li, Y., Bieker, G., & Mock, P. (2020). Real-world usage of plug-in hybrid electric vehicles: Fuel consumption, electric driving, and CO₂ emissions. *ICCT White paper*, 57.
- RTE. (2019). Integration of electric vehicles into the power system in France.
- Schuller, A., Flath, C. M., & Gottwalt, S. (2015). Quantifying load flexibility of electric vehicles for renewable energy integration. *Applied Energy*, 151, 335–344. <https://doi.org/10.1016/j.apenergy.2015.04.004>
- SDES. (2008). Enquête nationale transports et déplacements (entd) 2008. <https://www.statistiques.developpement-durable.gouv.fr/enquete-nationale-transports-et-deplacements-entd-2008>
- SNBC, D. (2019). Synthèse du scénario de référence de la stratégie française pour l'énergie et le climat - SNBC, 47.
- Soares, F., Lopes, J. A., Almeida, P., Moreira, C., & Seca, L. (2011). A stochastic model to simulate electric vehicles motion and quantify the energy required from the grid. *Power Systems Computation Conference (PSCC)*.
- Thompson, A. W., & Perez, Y. (2019). Vehicle-to-Everything (V2X) energy services, value streams, and regulatory policy implications. *Energy Policy*, 111136. <https://doi.org/10.1016/j.enpol.2019.111136>
- Yuksel, T., & Michalek, J. J. (2015). Effects of Regional Temperature on Electric Vehicle Efficiency, Range, and Emissions in the United States. *Environmental Science & Technology*, 49(6), 3974–3980. <https://doi.org/10.1021/es505621s>

3.A Summary of EV model input and output data and program parameters

In this appendix are listed the input parameters of the mobility model, along with their source:

- **Inside the model**, definition of macro parameters
 - Number of vehicle modelled in a Monte-Carlo simulation
 - Number of Monte-Carlo simulations (in order to parallelize the simulation)
 - Time step of simulation (typically hourly or 30 minutes)
- **Macro data on EV parameters**, sourced from the scenario of EV diffusion selected
 - Number of every vehicle type in the fleet (BEV, PHEV, FCEV)
 - Battery capacity of every vehicle type (average and standard deviation), in kWh
 - Repartition of connection behaviors inside the population, per vehicle type (between "systematic" connection, "when needed" or "when convenient")
 - Consumption per km of the vehicles studied, depending on driving speed and outside temperature
 - For long distance trips, the minimum battery capacity of vehicles suited for such trips, and the battery level threshold when BEV stop mid-trip and resume their trip (typically 20% and 80% respectively), which models the availability of charging points.
- **Macro data on charging infrastructure**, sourced from the scenario of EV charging infrastructure diffusion selected
 - Availability of charging points (as a percentage of vehicles that have access to a charging point) per location (at home, at work and public charging points)
 - Maximum charging power, in kW, per charging point location
 - Charging efficiency, the ratio between electricity withdrawn from the grid and stored inside batteries
- **Trip data**, sourced from our analysis of travel surveys
 - Set of trips for local mobility, per day (working day, Saturday or Sunday), per zone (rural, urban or largest cities) and per trip purpose (going to work, other purposes, either 2 or 4 trips per day). For each set, the list of daily distances, departure times and arrival times of each trip

- Set of trips for long distance, per trip purpose (holiday, work or visiting someone). For each set, the list of daily distances, departure times and arrival times of each trip
- Description of the daily purposes of daily mobility (e.g. for the purpose "commuting to work, 2 trips", first trip from home to work and second return trip towards home).
- Distribution of trip purposes per day type, zone and EV owner profile (employee, others)
- Distribution of EV owner profiles per zone

- **Calendar data**

- Share of vehicles driving local mobility and long distance trips each day of the year, based of our analysis of travel survey for the distribution of local mobility trips, and from our analysis of trip survey and highway traffic data for the distribution of long distance trips
- Average temperature in France at the hourly time scale, based on data from *Météo France*, for various weather year
- Share of vehicles driving long distance trips among long-distance trip purposes (holiday, work or visiting someone), as described in the French travel survey

Following this inputs, we list here the outputs of the model:

- **Summary of the simulation**, total annual EV electricity demand from the grid, gas consumption (PHEVs), H₂ consumption (FCEVs), total distance driven in local mobility and long distance trips.
- **For each time step t :**
 - Distance driven on the roads, detailed by travel segment (local mobility and long distance trips)
 - Total charging point power, battery capacity and number of all EVs that are available and connected to a charging point (those that were already connected before t and those that connects at t), detailed per connection to the grid behavior, vehicle type, charging point location (home, work, public) and zone (urban or rural)
 - Total charging point power, battery capacity and number of EVs that connect at time step t , similarly detailed
 - Total charging point power, battery capacity and number of EVs that disconnect at time step t , similarly detailed
 - Uncontrolled EV demand, detailed by connection to the grid behavior, vehicle type, charging point location, zone and charging point power

- Average EV state of charge, detailed by connection behavior, vehicle type and zone

- **For specific simulations:**

- Maximum EV charge per time window selected (e.g. between 14:00 and 17:00), by constraining EVs to charge preferably in this time window)
- Statistically representative results on long distance mid-trip demand, within simulations focused on long distance trips.

The program is built in the programming language R, and generates EV demand data for a whole year at the hourly time step, modelling 50 000 EVs (for statistical representativeness) in around 4 hours. Figure 3.10 illustrate the flowchart of the EV connection modelling methodology.

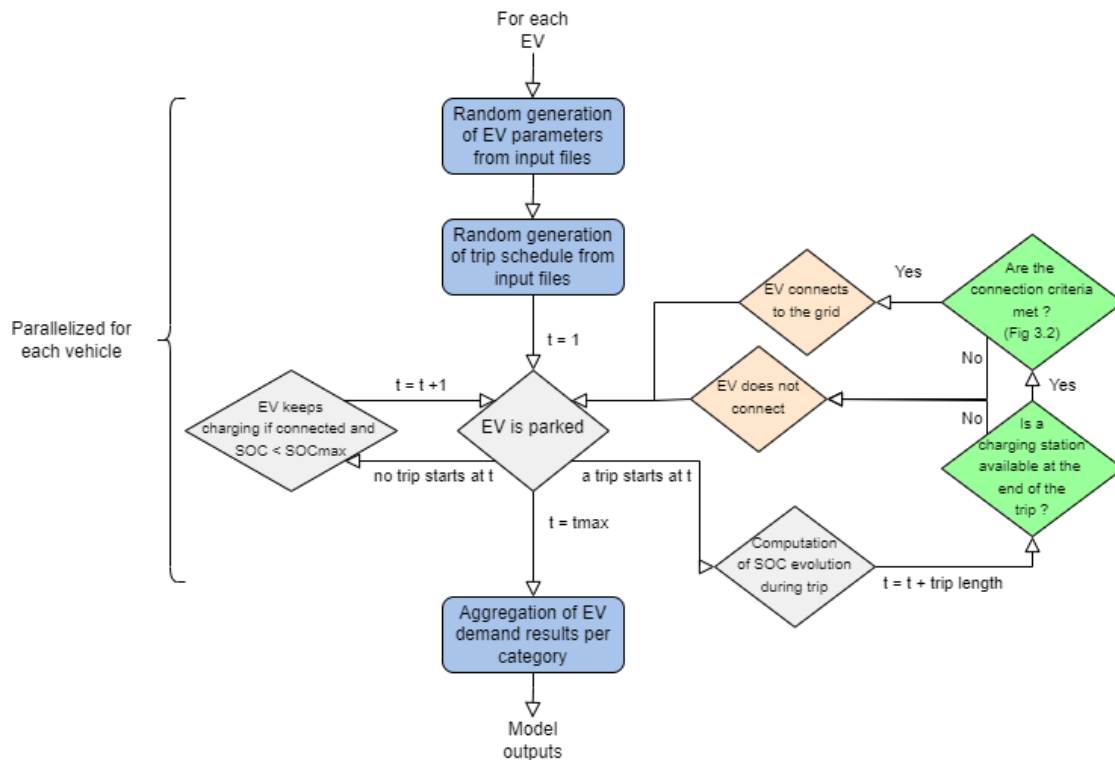


Figure 3.10: More detailed flowchart of EV demand generation methodology described through this Chapter

3.B Additional results

In this appendix, we illustrate additional results to those provided in section 3.3.

First, the maximum share of electricity demand that can be withdrawn in several time windows is shown in Figures 3.12 and 3.13, computed in specific EV demand modelling, by constraining EV to charge at maximum during the time window. The process added inside our EV model to compute maximum charging inside a given time window is explained in Figure 3.11.

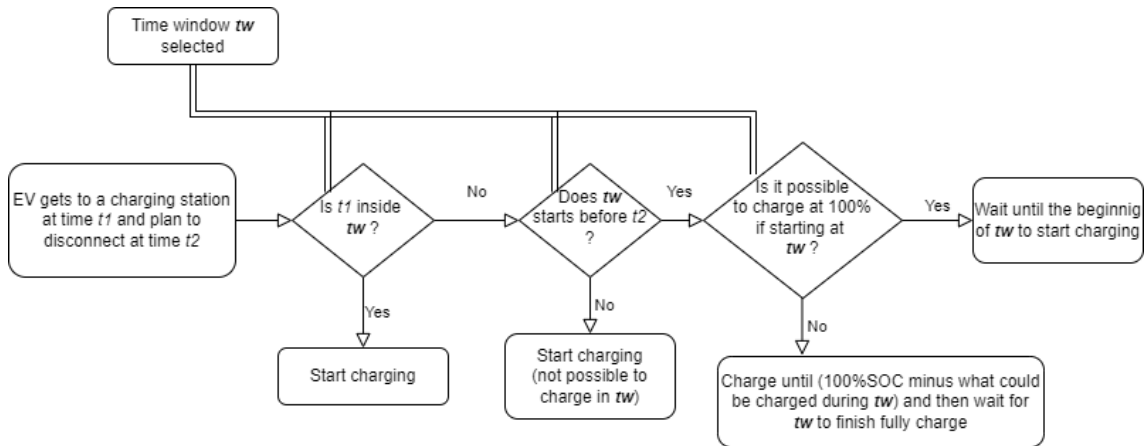


Figure 3.11: Flowchart of methodology used inside step 4 of our EV model in order to compute maximum charging in a given time window

The maximum demand for each 2-hour windows for the two main connection behaviors studied in this Chapter follow the same trend as the share of EVs connected through the day (Figure 3.12). It is to be noted that for the "systematic" connection behavior, the low energy demand per day per vehicle enables total EV charge to be concentrated at up to 60% during 2-hour time windows (at night).

As expected, maximum EV charging in time windows is not cumulative (e.g. the maximum share of energy charged between 13:00-17:00 is lower than the sum of the 13:00-15:00 and 15:00-17:00 maximum demand), as illustrated in Figure 3.13 for "systematic" connection. With our connection behavior assumptions and charging points available, up to 84% of the charge can be made in the evening and night, compared to up to 43% in the mid-day time window (11:00-17:00), at peak solar PV generation.

Then, the distribution of long distance trip demand on an averaged day is illustrated in Figure 3.14. Around 33% of long distance related EV charging is done mid-trip, at fast charging stations in our scenario. Long distance peak power demand happens slightly later than short distance trips, at around 21:00-23:00 as most of EVs are at or close to their destination by then, and most of them not fully charged yet.

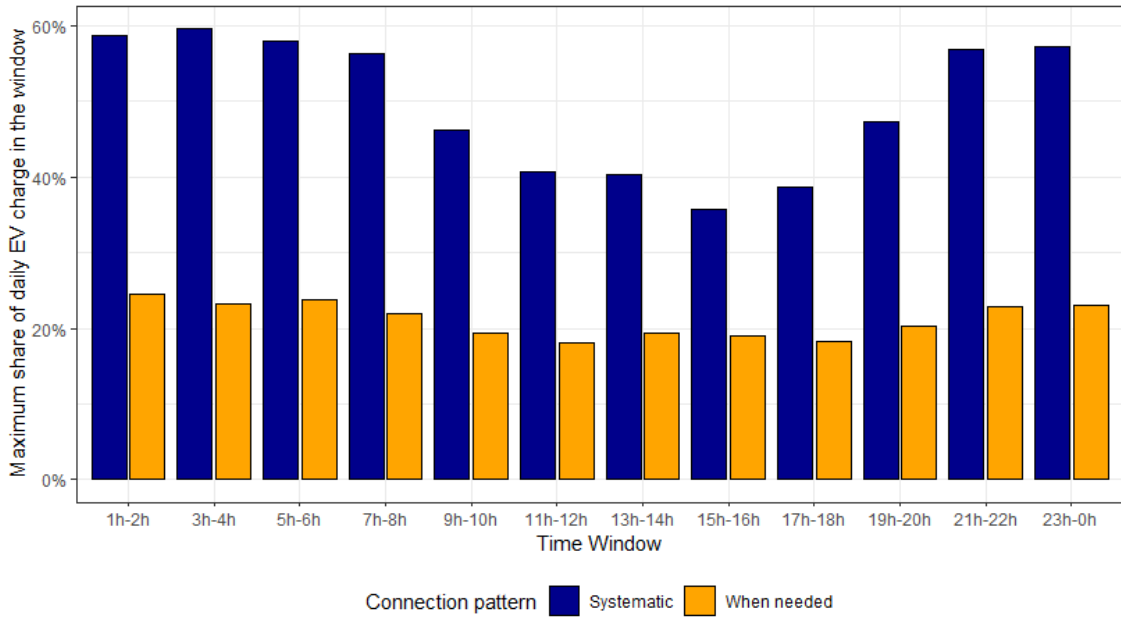


Figure 3.12: Illustration of maximum share of daily EV demand per time window throughout the day, the x-axis data being the time steps of our model, in such a way that 1h-2h means the time window between 1:00 and 3:00

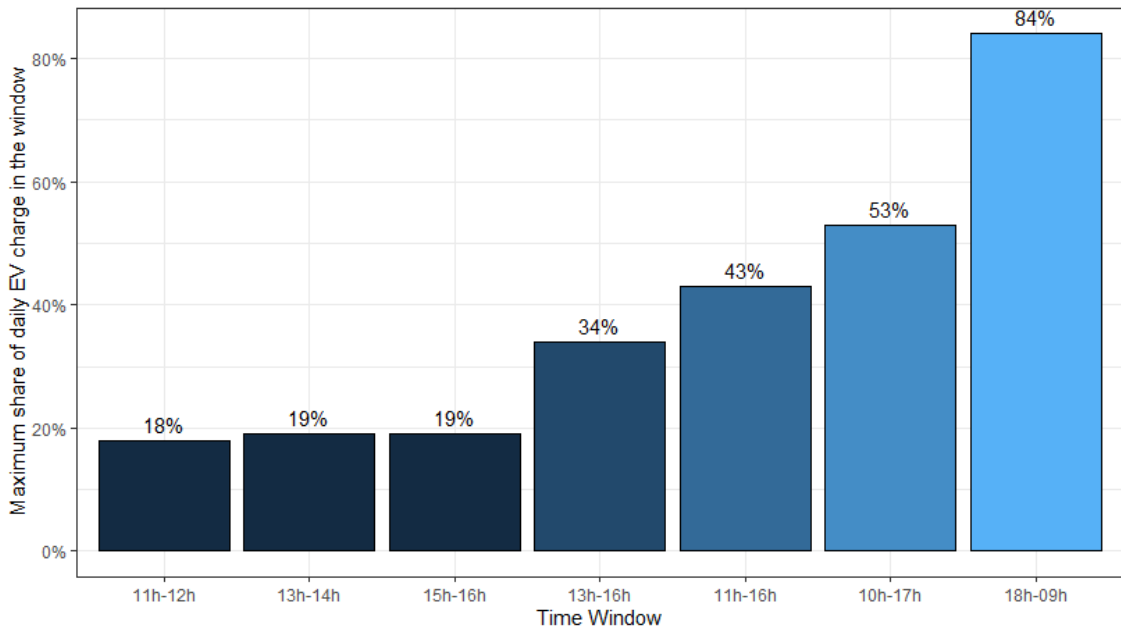


Figure 3.13: Illustration of maximum share of daily EV demand for different time window lengths, for the "systematic" connection behavior

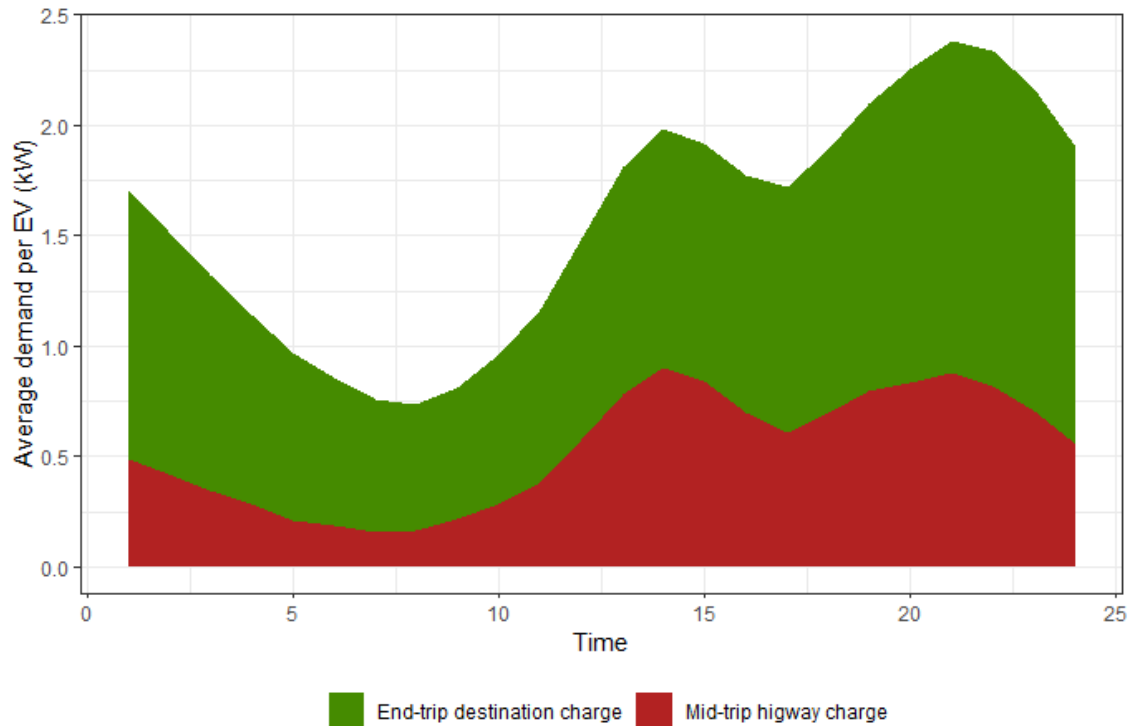


Figure 3.14: Repartition of long distance demand between mid-trip fast charging and charging at trip destination (stacked graph)

3.C Downscaling national results at the regional scale

This appendix addresses the issue of the possibility of using EV demand data, generated in this Chapter, at a smaller scale than average national data. This analysis makes it possible to estimate load curves by region or by city, depending on the scale of the transport grid to be studied. For more local load curves (at the electricity distribution level), other approaches, such as activity-based (as presented in Chapter 2) are more relevant.

A combination of top-down and bottom-up approaches will be presented here. First, the bottom-up approach relies on the fact that we divide travel data by area (rural, urban and largest cities) in our travel survey analysis, and thus in our model results, which allows us to obtain average data per vehicle for each of these types of areas. Second, the top-down part of our method is based on a downscaling of these results to the appropriate level.

With respect to the data used in this analysis, we can on the one hand obtain the distribution by department of past EV sales, which is a good indicator of the current location of EVs. On the other hand, we have the distribution of all individual vehicles currently by municipality, by multiplying the share of vehicles per

household and the number of households per municipality. ¹ From this data, we have a proxy of two EVs distributions:

- The current distribution of EVs by municipality in France. Within this, we can see that the wealthier departments are those with the most EVs. In 2019, 5.4% of individual vehicle sales were EVs in Paris and 4.4% in Bouches-du-Rhône, compared to less than 2% in the most rural French departments. This can be explained by several factors: areas with high EV development are usually higher income areas, with shorter and slower vehicle trips (better suited to EVs) and where low emission zones are set during pollution peaks.
- The theoretical distribution of uniform EV diffusion within the population (similar to vehicle ownership if there is no major change in urban planning).

To estimate the distribution key between these two temporal horizons (2020 for the first and 100% electrification for the latter), the following model can be used as a first approach: weighting *current distribution* key by $(1 - \text{electrification rate})$ and *uniform distribution* key by the electrification rate.

To improve this estimate of the prospective distribution of EVs within the population, we recommend a model of the individual vehicle fleet, particularly within income deciles, and taking into account the second-hand market model.

3.D Heavy mobility demand modeling

Additionally to individual vehicles that are the core topic of this Chapter, the mobility model built enables the study of electric demand of other electric vehicles. As described in the introduction, the demand of electric scooters and electric bikes is not expected to reach a significant amount of total consumption, so a precise modeling of those vehicles does not seem relevant. However, electric or plug-in hybrids trucks and buses could reach a large share of respectively freight and passenger transport. As a consequence, the adaptation of our model and data to study the electrification of those transport means is described in this appendix.

3.D.1 Buses

To begin with, buses can be classified as "local mobility" defined in this Chapter, as they do not usually drive long distances during a day. As identified in section 1.2.2, several smart charging modes could emerge for electric buses: plug-in charging at the depot, mid-trip charging (catenary or induction) or fast chargers at the terminal. Charging only at the depot requires larger battery capacities than the other solutions.

¹For France, these data can be found in the studies *Données sur les immatriculations des véhicules, Couples-Familles-Ménages en 2017* and *taux de motorisation des ménages* of INSEE

On the one hand, modeling electric buses that charge at the depot each night could rely on the same methodology as individual vehicles that perform local mobility trips and are charged at home. This charging location enables electric buses demand side flexibility, provided the charging powers are high enough.

On the other hand, mid-trip charging could be approximately modeled as an electric consumption (from the electricity grid) close to the consumption of the vehicle on the roads.

Finally, a major limitation to the study of electric buses grid integration is the lack of public open-source data about bus trip characteristics (distribution of bus trip lengths and return times to the depot). Indeed, most travel survey focus on the trips of *individuals* rather than the trips of *vehicles*, which is not a problem for personal vehicles, as these data match, but it is not the case for public transportation, as individuals hop on and off the vehicles. One solution could be using timetables of bus routes (public and easily accessible) in order to estimate distances and trip times of buses, although timetables do not indicate which buses are used through the day or if they go back to the depot at mid-day.

The same observation applies to other transport segments close to public buses described in this Chapter, such as school buses and coaches that make city-to-city trips.

3.D.2 Trucks

First, when it comes to trucks, it is even harder to get reliable trip data, as neither travel surveys displaying trip data (as individual vehicles) or public timetables (as buses) were found. A large majority of trucks belong to private operators, which might be less willing than others to collaborate with academics by sharing their datasets.

Trucks can be classified in several groups: rigid trucks, semi-trailer trucks and smaller trucks for local delivery. The study of each of them requires analysis on which trips are to be made, and what are the characteristics of the electric trucks (heavier vehicles, which implies larger consumption, for long distance semi-trailer trucks for instance).

Similarly to buses, several smart charging modes could emerge for electric trucks: plug-in charging at the depot, mid-tip fast charging (during driver breaks), or even dynamic charging while driving (some electric road trials were launched recently).

For mid-trip fast charging, similar modeling as for long distance trips of individual vehicles could be applied, while night charging at the depot for local delivery trucks requires similar methodology as what is defined as local mobility in this Chapter.

4 - Chapter 4: Electric vehicle flexibility from national hourly supply-demand adequacy

Summary

Electric vehicles (EVs) are expected to grow massively in the coming years, and grid integration of a large number of them could challenge electricity-system infrastructure. This Chapter proposes a methodology to study the technical and economic impacts of mass EV charging on power systems, based on EV connection and charging needs generated through the methodology of the previous Chapter (which allows to generate uncontrolled demand). This framework is applied to a case study at hourly resolution of high penetration of electric vehicles and renewable energy sources in Europe at the 2040 time-horizon, in line with the 'National Trends Scenario' grid mix under the pan-EU ENTSO-E Ten-Year Network Development Plan. Results show that the European electricity system can accommodate large EV growth and that widespread adoption of smart charging in France can significantly reduce operational electricity system costs by up to 1.1 G€ and reduce carbon emissions by up to 3.2 MtCO₂ per year. We also compare multiple EV smart charging modes of vehicles in France, and identify which parameters have the largest impact on EV flexibility, including gas prices, smart charging adoption, weekly flexibility, and mid-day charging.

4.1 Introduction

This Chapter is focused on the interaction between EV charge and the hourly operation of the rest of the power system (generating units, storage, interconnection). This field of study does not usually consider electricity transmission grid congestions inside a price zone, but the neighboring countries have to be modelled in order to model flexibility from cross-border exchanges. Some authors have studied the impact of EV charging on such similar scopes. Wulff et al. (2020) modelled EV flexibility, smart charging and vehicle-to-grid (V2G) for the German power system by linking an existing transport model and a power system model (REMIX), and they showed that EV load shifting reduces renewable curtailments as a function of charging power and EV behavior. Wolinetz et al. (2018) also applied a similar methodology to study the optimal investment path towards 2050 for different EV flexibility scenarios and found that developing smart charging reduces the need to invest in flexible generation capacities. Liu et al. (2014) analyzed a scenario of full electrification of personal vehicles and its impact on the spot market in Nordic countries, while Robinius et al. (2017) followed a similar methodology for the case of FCEVs to estimate the hydrogen supply infrastructure that would be needed to accommodate high FCEV development.

In this work, we attempt to complement the extant literature on this topic by providing a methodology and case study on EV adoption at national scale and to

a prospective horizon. The main contributions of this Chapter are a methodology adapted for other power-system software and sensitivity studies on two of the main factors shaping the integration of a large share of EVs: the connection behavior of EV owners, and the diffusion of multiple smart charging techniques. Socio-economic surveys currently observe multiple connection behaviors of EV owners (Enedis, 2020; Soares et al., 2011), ranging from connecting the vehicle as much as possible to charging it only when necessary, on a weekly basis or even less frequently. Moreover, as driving range is one of the main barriers to EV development (along with strong charging-station system coverage) (Funke et al., 2019), car manufacturers are currently working on extending the autonomy of EV batteries, which could make EV connections to the grid less frequent in the years to come. The second main factor affecting the flexibility offered by EVs studied in this work is the adoption of smart charging. In case of high social acceptance of smart charging (unidirectional or bidirectional), EVs could provide a significant source of demand-side flexibility and thus decrease EV charging costs compared to uncontrolled charging of these vehicles. We identify a wide range of smart charging approaches that can be modelled, providing either daily or weekly demand flexibility.

This Chapter is structured as follows. First, we introduce in section 4.2 the methodology developed to study the integration of EVs in supply-demand adequacy models along with the smart charging modes that our model enables the study of, with a focus on time-of-use charging in subsection 4.2.4. Second, we present and discuss the results of a case study on the integration of EVs into the European power system to the 2040 time-horizon in section 4.3, while providing insights on which parameters have the biggest impact on EV flexibility provision. Third, those results are further discussed in sections 4.4, before concluding the Chapter in section 4.5.

4.2 Electric vehicle smart charging modeling in power system adequacy models

4.2.1 Power system model selection

As mentioned in the introduction section, different dimensions of the electrical system interact with EV charging, which means that EV smart charging can be controlled from multiple perspectives. Large EV market penetration implies that individual EV consumption could reach a significant share (up to 15%) of total electricity consumption in the mid-term. Therefore, considering EVs as price-takers in prospective studies (which means using electricity market data exogenous to EV charge) is a major approximation. To go beyond this price-taker hypothesis, EV demand data has to be integrated in a power system modeling framework. Below we describe the approaches found in the literature, depending on the scope of study.

First, studying the optimal year-by-year investment into new generation and flexibility capacities can be studied with capacity expansion models (see Foley et al. (2010) for a review of such models). The advantage of this type of model is to evaluate the dynamics of technology diffusion, but at the cost of lower accuracy on intraday flexibility (often studying a set of time slices). In this field, Borozan et al. (2021) and Wolinetz et al. (2018) study how much the optimal investment in new capacities differ whether EVs are smartly charged or not.

Second, generation and transmission system operation models (often called ‘unit commitment and dispatch’ models) are built to study load-generation adequacy or large systems (spanning several countries or regions) while considering the transmission capacities between them for given electricity generation capacities, flexibility assets, and base demand data. These models can be used to study how valuable flexibility of EV charge is for electricity supply and demand at national scale and its impacts on carbon emissions and electricity prices. These models become more and more useful for studying EV flexibility in scenarios with higher wind and solar generation capacities, as ‘valley filling’ becomes further from the less costly and less CO₂-emitting solution for EV charge.

The third option is to study the electrical system with a sharper description of the physical aspects of electricity transmission and distribution networks, with or without the DC power flow simplification and possibly including voltage constraints or dynamics. This comes at the cost of limiting the area of study (a country or a smaller region) and the length of the period studied, as compared to generation system operation models. Most studies of the interaction between EVs and distribution grids rely on this modeling approach, especially when scoped at the local scale (Fischer et al., 2019; Green et al., 2011; Jarvis & Moses, 2019; Mehta et al., 2019) while very few have studied the impact of EVs on transmission grids (Slednev et al., 2021).

In this work, we chose to study EV flexibility from the second perspective (‘unit commitment and dispatch’), as it has been identified as one of the main research gaps for mid-term studies (Arvesen et al., 2021; Schill & Gerbaulet, 2015). Among the unit commitment and dispatch models available (e.g. PLEXOS, UPLAN, EMPS), we selected AntaresSimulator (“AntaresSimulator,” 2022), which is an open-source model in which a base study of the European electricity system in 2040 had already been built and was readily accessible. However, the EV aggregation methodology and formulation of optimization constraints described in the following section could be adapted for other software. AntaresSimulator aims to minimize the total operational cost of a given electricity generation and consumption system while ensuring supply can adequately match demand adequacy, from a ‘perfect foresight’ perspective, under the optimization function below:

$$\min \sum_t \sum_z P_{z,t} * MC_{z,t} + \delta_{z,t}^+ * G_{z,t}^+ + \delta_{z,t}^- * G_{z,t}^- \quad (4.1)$$

where t is the time step, hourly in our case study, z is the price zone, and for each in zone z and time t , $P_{z,t}$ is the electricity generation, $MC_{z,t}$ is the marginal

generation cost, $G_{z,t}^+$ is the unsupplied energy ("loss of load"), $\delta_{z,t}^+$ is the cost of unsupplied energy, $G_{z,t}^-$ is the renewable energy curtailment, and $\delta_{z,t}^-$ is the cost of energy curtailment. The full formulation of the optimization problem can be found in Doquet et al. (2011) and on the software webpage ("AntaresSimulator," 2022). It simulates the electrical system for a whole year at hour-by-hour resolution and computes an hourly electricity marginal generation cost at the intersection of the supply and demand curves, while also modeling the constraints of thermal power plants (ramping constraints, start-up costs and minimum up-time), the variability in solar PV and wind generation via a set of weather data, and the optimization of hydro storage plant generation through the year. On the other hand, some simplifications are made, due to the hourly time step, on the dynamics of the power system. The European power network is also approximated at the national scale, with capacities between price zones, but congestions inside a price zone are not modelled here.

The zones considered in this work are 37 price zones of Western and Central Europe, with some countries corresponding to a single price zone (e.g. France, Spain, Germany and Belgium) while others are split into several price zones (e.g. Italy and Norway). The area selected is identified in Figure 4.1 and gathers most of the synchronous grid of Continental Europe, as well as the UK, Ireland, Scandinavia and the Baltics.

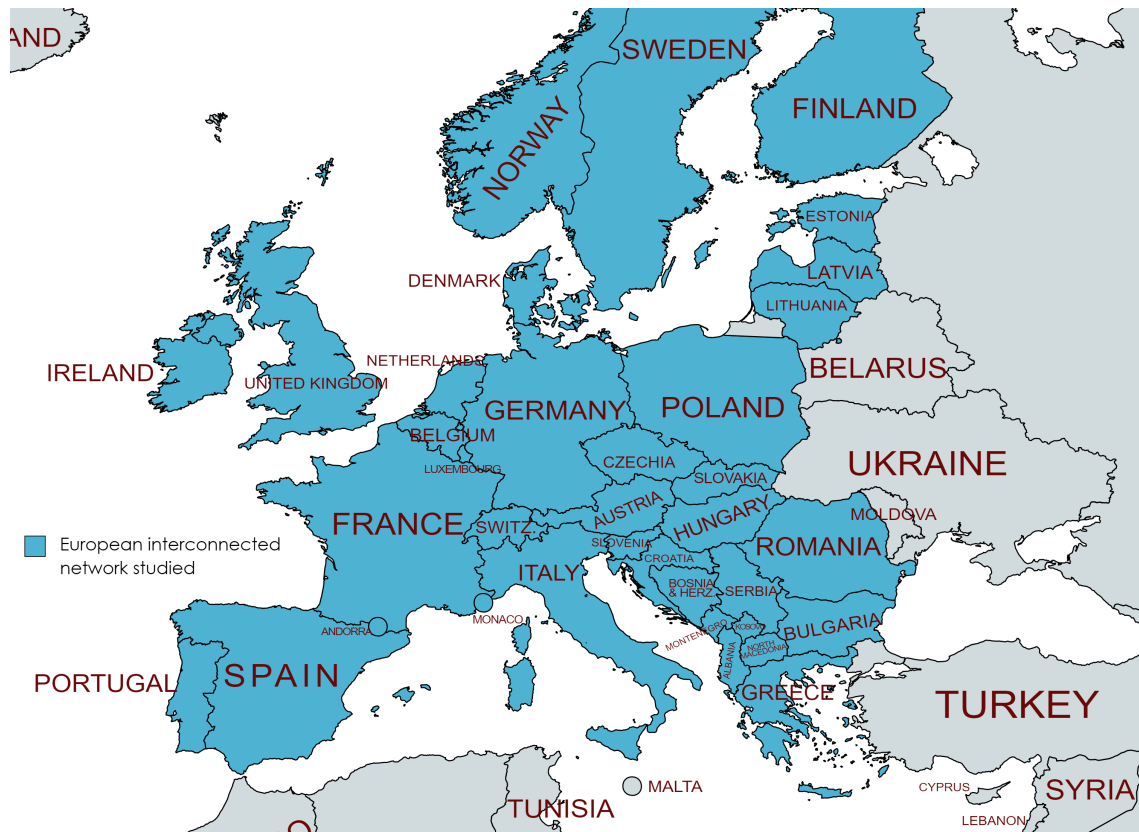


Figure 4.1: European countries in the area studied

A key asset of AntaresSimulator for modeling EV flexibility is that it enables the addition of custom sets of constraints to model several EV smart charging modes, as described in the following sections. The data processed through AntaresSimulator in our methodology is described in Figure 4.2.

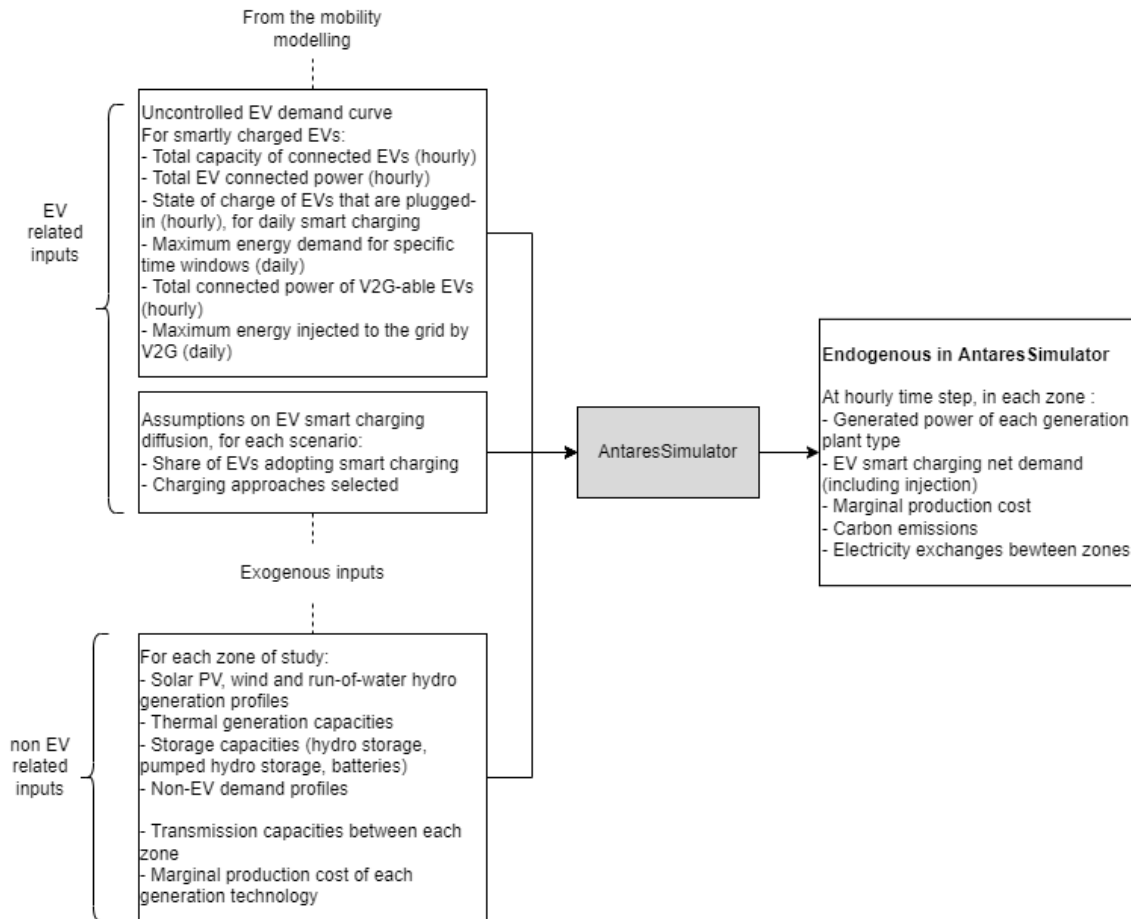


Figure 4.2: Inputs and outputs of our electrical system modeling process

4.2.2 EV aggregation for EV flexibility modeling

In order to integrate widespread adoption of EVs into a power system model, it is necessary to aggregate the vehicles into a limited number of equivalent objects, as power-system models cannot independently model the several million EVs that are expected to be on the roads in Western Europe in the mid-term (2030 to 2040). In order to do so, Ried et al. (2020) and Wulff et al. (2020) reviewed some of the following approaches that are being used in the EV literature.

On the one hand, a significant share of the EV literature aims to precisely aggregate the charge of a limited number of EVs at the local scale. Some studies consider independently every charging events, which is not scalable. Wu and Sioshansi (2017) introduce an operational heuristic for the optimal placement of multiple EVs charge at a charging station level, modeling well the constraints of

multiple EV flexibility. However, electricity prices are exogenous from the optimization, which implies that this approach is not suited for our case study. The same observation is made on the methodology from Wang et al. (2021), in which the rolling window approach concentrates on the stochastic EV connection and demand, but cannot be easily coupled to power system modeling.

Second, some studies model EV flexibility by computing the maximum SOC curve (EVs that charge as soon as possible) and the minimum SOC curve (EVs that charge as late as possible, in order to leave with a battery fully charged) for each vehicle. The charging algorithm then select the optimal aggregated charging profile constrained between the total minimum and maximum SOC curves (Cai et al., 2018). In a similar fashion, Barot and Taylor (2017) proposed a more complex and exact mathematical consideration of EV flexibility boundaries that employs Minkowski sums to aggregate the charging constraints of a multiple EVs. Unfortunately, this approach is not applicable to our study of millions of EVs in a power system model.

Ultimately, the best approach identified for the problem studied here is to model EV fleets as an equivalent battery, while adding constraints to the optimization problem so that the mobility needs of EVs, and the evolution of their connection, on-road consumption and recharge needs are modelled. This choice was advocated by Ried et al. (2020). The methodology and limits of our EV aggregation solution are presented in the subsection 4.2.3.

The aggregation of EVs as proposed in this Chapter was made possible by the fact that we had modelled EV connection and demand beforehand. This methodology might not be easily applicable based on only average values of EV departure times and daily energy demand.

4.2.3 Modeling EV smart charging inside a power system simulation tool

It has long been known in the battery literature that lithium-ion batteries lose some of their charging power is when their state of charge is close to 100% (Pelletier et al., 2017). However, in this work, as we are studying aggregated EVs at the hourly time-scale, EV battery charge is approximated as linear in time at its constant rated power.

The focus of this case study is to study the impacts of EV charges in France on the European power system. As a result, in the modeling implemented for this study, all EV-related parameters are geared to the French zone. The methodology can be scaled up to pan-European level with a set of equations for multiple zones if EV input data is generated similarly for the other zones. In addition, the following EV equation and parameters only relate to EVs that accept charge management. Other 'uncontrolled' EVs, whose charging is modelled using the methodology described in Chapter 3, are added to the non-flexible demand. The charge of flexible EVs, referred to as "smart charging", is determined by AntaresSimulator: it is considered as one of the many decision variables of the operational cost minimisation

problem.

In the specific case of modeling EV smart charging inside our model, the major output decision variable of our methodology is EV demand on the power network at each time-step C_t^{EV} , while the other decision variable required to ensure that EVs are sufficiently charged is the energy stored in EVs connected to the grid, named ES_t^{con} (in kWh), is equivalent to state-of-charge (in percentage) multiplied by the battery capacity (in kWh).

The relation between these two variables is found by using two different equations to write the evolution of the state of charge of every vehicle in the simulation. First, the evolution of EV aggregated charge level can be split between connected and disconnected vehicles,

$$\Delta ES_t^{allEV} = ES_t^{allEV} - ES_{t-1}^{allEV} = \Delta ES_t^{con} + \Delta ES_t^{unc}, \forall t \quad (4.2)$$

where ΔES_t^{allEV} is the variation between two consecutive time steps of the stored energy stored across all EVs, ΔES_t^{con} is the variation in stored energy stored in EVs connected to the grid at time t, and ΔES_t^{unc} is the variation in stored energy in EVs that are not plugged in. Then, as we consider that during our simulation, the number of EVs is constant,

$$\Delta ES_t^{allEV} = C_t^{EV} - D_t^{EV}, \forall t \quad (4.3)$$

where D_t^{EV} the electricity consumption of vehicles on the road. As a result, when fitting equation 4.3 into equation 4.2,

$$\Delta ES_t^{con} = C_t^{EV} - (D_t^{EV} + \Delta ES_t^{unc}), \forall t \quad (4.4)$$

which is the main equation that links ES_t^{con} and C_t^{EV} , while the third term ($D_t^{EV} + \Delta ES_t^{unc}$) reflects the variation on stored energy in the connected vehicles induced by the disconnection of fully charged EVs and the connection of some EVs at the end of their trips. This last term is exogenous to EV charging strategies and is therefore computed prior to the simulation by our EV trip and connection module (see section 3.2.6).

C_t^{EV} , the EV demand on the power network, can be negative in settings that use grid injection from vehicles that allow V2G,

$$C_t^{EV} = \eta_w * CW_t^{EV} - 1/\eta_i * CI_t^{EV} \quad (4.5)$$

where η_w is the efficiency of electricity conversion for grid withdrawal, η_i the efficiency of electricity conversion for grid injection, CW_t^{EV} the electricity withdrawn from the grid, and CI_t^{EV} the energy injected into the grid.

The additional constraints for EV flexibility are defined as follows:

$$Capa_t^{con} * SOC^{min} \leq ES_t^{con} \leq Capa_t^{con}, \forall t \quad (4.6)$$

$$C_t^{EV} \leq P_t^{con} * \tau, \forall t \quad (4.7)$$

$$\sum_{t \text{ in day}} C_t^{EV} = C_{totday}, \forall day \quad (4.8)$$

$$\sum_{t \text{ in } tw} C_t^{EV} \leq C_{max_{tw}}^{EV}, \forall tw \quad (4.9)$$

$$CI_t^{EV} \leq P_t^{con, V2G} * \tau, \forall t \quad (4.10)$$

$$\sum_{t \text{ in day}} CI_t^{EV} \leq CI_{max_{day}}^{EV}, \forall day \quad (4.11)$$

Equation 4.6 ensures that the energy level stays between the maximum total capacity of connected EVs, $Capa_t^{con}$, and a minimum state of charge SOC^{min} that reflect a ‘safety-buffer’ state-of-charge that needs to be kept in EV batteries in the event of unexpected mobility needs (aggregated for all EVs). Typical selectable SOC^{min} values range from 20% to 40% depending on average battery capacity. Equation 4.7 limits the power that can be withdrawn from the grid at any time-step below the total charging power of connected EVs, P_t^{con} , computed by the mobility model, times the time step selected τ .

In most studies on EV smart charging, each charging session is constrained to reach a 100% state-of-charge before the vehicle leaves. To do so, when aggregating a large pool of vehicles, equation 4.8 forces the optimization to withdraw, each day, as much energy as in the case of an uncontrolled charge scenario C_{totday} . Note that in order to match an EV connection pattern in which a significant share of charging time windows are spread over the night (typically 18:00 to 07:30), the “day” can preferably be selected from 08:00 to 08:00 in equation 4.8. Heggarty et al. (2020) showed that flexibility is a multi-timescale topic that can be classified into three sections: annual, weekly, and daily flexibility. Under equation 4.8, EVs are limited to daily flexibility only. However, as battery capacities are tending to expand, a significant share of EVs might soon be able to be used for daily commutes for nearly a week before the need to be fully charged again. As a result, equation 4.8 can be disabled to study the potential of weekly EV flexibility.

One of the major limits to aggregation identified when modeling EV charge with only the previous constraints is that on some days, all the daily smart charging demand could be satisfied in a limited number of time-steps, especially at midday which correlates with peak solar PV generation. However, looking at the individual EV patterns that were generated by our mobility model, some EVs are only connected at night (e.g. between 18:00 and 07:30) while others are connected at work during the day (e.g. between 08:00 and 17:00). As a result, some of the smart charging load curves initially computed (without this constraint) showed all the electricity withdrawn by EVs between 10:00 and 15:00, which is highly unrealistic (way over the share of EVs connected in this time window, which is one of the limit of aggregating EVs into a single object in the model). To overcome this issue, equation 4.9 was added to our optimization problem. For various selected time-windows tw , we limit EV charge to the maximum possible energy withdrawal

from the grid in that time window $Cmax_{tw}^{EV}$, which is computed from our mobility model as the share of energy withdrawn in that time-window when individual EVs try to maximize it. The specific time-windows selected and typical values for their maximum energy demand are described in section 4.3.1.

Finally, equations 4.10 and 4.11 are added to study V2G: Eq. 4.10 ensures that energy injected by those vehicles to the grid CI_t^{EV} is bounded by the total connected power of EVs allowing V2G $P_t^{con,V2G}$, while Eq. 4.11 limits each day's amount of energy injected back to the grid below CI_{day}^{EV} . This constraint is set based on the user acceptance of additional cycling of EV batteries for grid flexibility (typically 1 additional cycle per month, 1 additional cycle per week, or no limit on grid injection). For instance, if we allow 1 additional cycle per week, the maximum total energy injected each week is the sum of battery capacities of V2G-able EVs, which is distributed among the days of the week in proportion to the number of vehicles that get connected.

To summarize the EV smart charging modes enabled by our model, Table 4.1 indicates the set of equations to be enabled for each case.

Constraint	Unidirectional smart (daily)	Unidirectional smart (weekly)	V2G (daily)	V2G (weekly)
4.6	X	X	X	X
4.7	X	X	X	X
4.8	X		X	
4.9	X	X	X	X
4.10			X	X
4.11			X	X

Table 4.1: Constraints activated according to charging mode selected

Variable	Description	Unit	Source
C_t^{EV}	Net EV consumption from the grid	kWh	Optimized inside Antares-Simulator
$Capa_t^{con}$	Total EV capacity connected	kWh	Mobility model (chap 3)
$Cmax_{tw}^{EV}$	Maximum EV demand in time window tw	kWh	Mobility model (chap 3)
$Ctot_{day}$	Energy to be charged in day for daily flexibility	kWh	Mobility model (chap 3)
CI_t^{EV}	EV injected power to the grid	kWh	Optimized inside Antares-Simulator
$CI_{max_{day}}^{EV}$	Maximum energy injected each day by V2G	kWh	Assumption
CW_t^{EV}	EV withdrawn power from the grid	kWh	Optimized inside Antares-Simulator
ES_t^{allEV}	Total energy stored in all EVs	kWh	Optimized inside Antares-Simulator
ES_t^{con}	Total energy stored in connected EVs	kWh	Optimized inside Antares-Simulator
ES_t^{unc}	Total energy stored in unconnected EVs	kWh	Optimized inside Antares-Simulator
D_t^{EV}	Energy consumption of EVs on the road	kWh	Mobility model (chap 3)
η_i	EV injection efficiency (to the grid)		Assumption
η_w	EV withdrawal efficiency (from the grid)		Assumption
P_t^{con}	Total EV power connected	kW	Mobility model (chap 3)
$P_t^{con,V2G}$	V2G-able EV power connected	kW	Mobility model (chap 3)
SOC^{min}	Minimum state-of-charge to be kept in batteries	%	Assumption
τ	Time step of the simulation	hour	Selected

Table 4.2: Parameters of the EV charging module inside electricity production cost model

4.2.4 Time-of-use charging

In addition to the smart charging modes described in the previous section, EV load can also be controlled through static tariff signals, in which a smart meter charges the battery during predefined low-price periods. Electricity unit commitment and dispatch models do not directly compute such EV charging patterns, but the results of smart charging simulations are useful for understanding the optimal periods for EV charge.

Various time-of-use charging profiles can be found in the literature. On one hand, when considering a limited number of EVs or a basic approach for large EV fleets, some studies introduce a time-of-use charging mode by delaying the start of all EV charging sessions by one or a few time-steps, after peak demand (Arvesen et al., 2021; Liu et al., 2014; Xydas et al., 2016), which does not induce a second peak as long as EV time-of-use demand equals a few percents of total consumption. On the other hand, aggregating a large number of EVs with different time signals spread through several locations or contracts makes it possible to create an “improved” time-of-use load curve (RTE, 2019). In the same spirit, Li et al. (2016) assesses how to create more optimal time-of-use tariffs at the local scale by creating clusters of consumers to study the best low price windows. One way to build this kind of time-of-use demand curve is to compute the daily averages (possibly split between weekdays and weekends, and between seasons) of a smart charging demand curve, as computed with the methodology described above. The “improved” time-of-use curve would then be generated by applying the daily pattern to the total energy consumption of each day from the input data, in order to better consider solar generation than the “basic” approach. Those two approaches for building time-of-use tariff EV demand curves are illustrated in Figure 4.3.

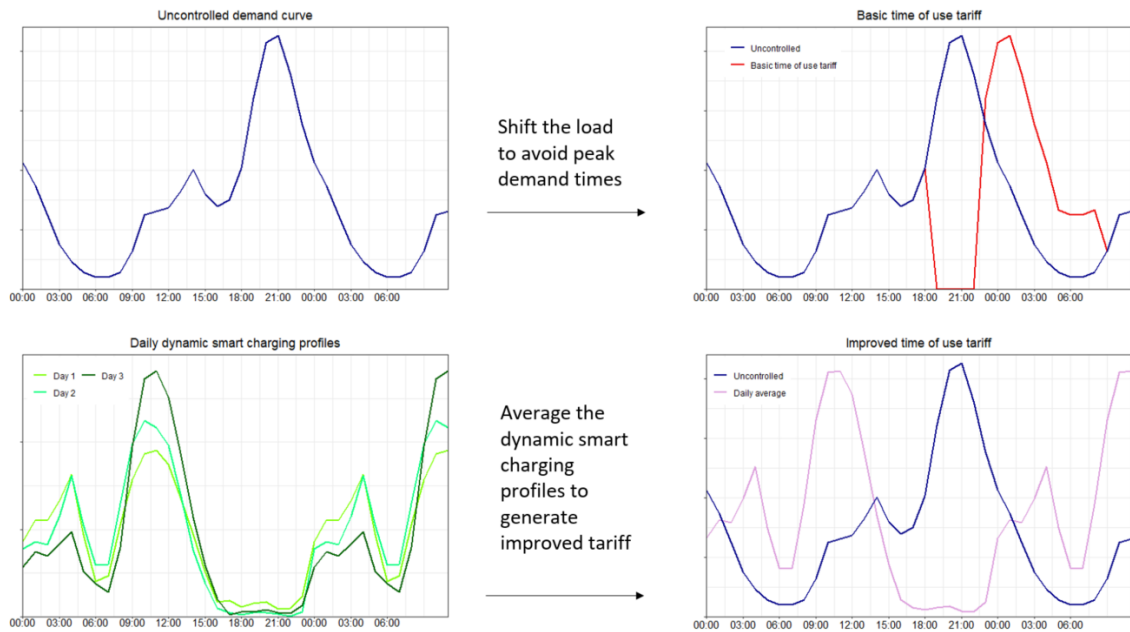


Figure 4.3: Illustration of the generation of Time-of-use profiles

4.3 Case study: electric vehicles and generation-load adequacy in Europe in 2040

4.3.1 Data and assumptions

European electricity generation and transmission system scenario

For this case study we selected the same prospective analysis of the integration EVs in 2040 as studied in the case study of Chapter 3. In addition to the transportation system, the whole electricity generation mix in Europe is also expected to shift towards decarbonization over the coming decades, with a growing share of electricity generated from renewable sources. Here we selected the National Trends Scenario from the 2020 ENTSO-E Ten years network development plan (TYNDP), at the 2040 time-horizon, as electricity generation mix data for this study (ENTSO-E, 2020a). In this scenario, renewable electricity generation reaches 73% of generated electricity (42% wind, 15% solar and 16% hydro) in the European countries studied (zone illustrated in Figure 4.1). The investment paths for electricity generation and transmission to 2050 for this scenario are described for each country in additional files on the ENTSO-E website (ENTSO-E, 2020b). In this scenario, France, for instance, is set to grow electricity generation from renewables from 21% to 65% between 2018 and 2040, while nuclear will decrease from 72% to 34% and other thermal sources from 7% to 1% (see Table 4.3).

Technology	2018 (Historical data)	2040 (National Trends Scenario)
Wind	5.1%	39.3%
Solar	1.9%	12.5%
Hydro	12.5%	12.7%
Other renewables	1.6%	0.8%
Nuclear	71.7%	34%
Gas	5.7%	0.7%
Other thermal	1.5%	0%

Table 4.3: Evolution in share of electricity generated by technologies in France between 2018 and 2040 (National Trends scenario)

Electric vehicle development in France in 2040

Regarding EV development scenarios, as we rely on the EV modeling methodology described in the previous Chapter, the assumptions on EV parameters chosen for our case study are similar to those in section 3.3.1.

Additionally, our mobility models can also serve to compute maximum energy consumption in various time windows, to be used in constraint 4.9 of our EV flexibility aggregation methodology. Based on most common mobility patterns found in the results of Chapter 3, two time-windows were arbitrarily selected in which EV charging is limited (below a value computed with the model described in Chapter 3): the mid-day time window (10:00 - 15:00), which matches peak solar generation, and the night-time window (17:00 - 08:00) in which EVs connected at home are usually charged. Maximum share of EV charge in these windows was 57% of demand in the mid-day time-window as "systematic" connection (resp. 40% as connection "when needed") and 81% of demand in the night-time window (resp. 73%).

4.3.2 EV smart charging results

For all results presented in the following sections, only the flexibility of EVs located in France is modelled. The load and flexibility of EVs in other countries are kept similar in all of the results presented here as the way they were modelled in the initial simulation (uncontrolled load, plus an equivalent battery, to take into account demand side flexibility). However, adding flexibility to the electricity system in one country also reduces operational costs and carbon emissions in neighboring countries. There are many indicators that can serve to analyze EV demand flexibility, including the annual operational cost in France or in Europe, carbon emissions, France's electricity trade balance, renewable energy curtailment (especially solar and wind), gas and oil-based electricity generation, the loss of load probability and amount of unsupplied energy. In our case study, as all these indicators follow the same trends, we mainly present the total European operational cost and carbon emissions, which are the most relevant for our analysis of the impacts of EV charge on the European electrical system.

In this work, we aggregated every EV of the simulation inside only one object of the proposed methodology, including PHEV (due to the low share of vehicles being PHEVs in our case study). However, one could separate EVs into several such clusters with their set of equations and input data, especially to distinguish between PHEVs, private BEVs and company BEVs in order to compute the flexibility potential of these vehicle types separately.

The methodology relies on climate data of 35 representative weather years, which helps taking into account the variability of these results according to yearly weather conditions. Results presented in this Chapter are averaged over those 35 weather year data.

These analyses allow us to estimate the value of EV flexibility for the power system but not to directly deduce the benefit for users, which depends on fixed costs in the electricity bill, taxes, and a potential share of the smart charging revenue for a third-party actor (i.e. aggregator).

Connection behaviors

To begin with the analysis of the results, we study the diffusion of EV smart charging (daily flexibility) by 20% increments, for two connection behaviors introduced in section 3.2.7: "systematic" connection and connection "when needed". 20% increments were selected to illustrate the effects of smart charging diffusion as we do not expect strong discontinuities within these increments. As identified earlier and illustrated in Figure 4.4, occasional charging is preferable for uncontrolled EVs, as the charging sessions are less synchronized. However, the higher the number of vehicles that adopt unidirectional smart charging, the more preferable it becomes that EV owners connect their vehicle systematically. Smart charging 24.4 million EVs in France reduces annual carbon emissions in Europe for electricity generation by 2.4 MtCO₂ (0.6%) in the connection "when needed" scenario, and by 3.2 MtCO₂ (0.9%) in the "systematic" connection scenario.

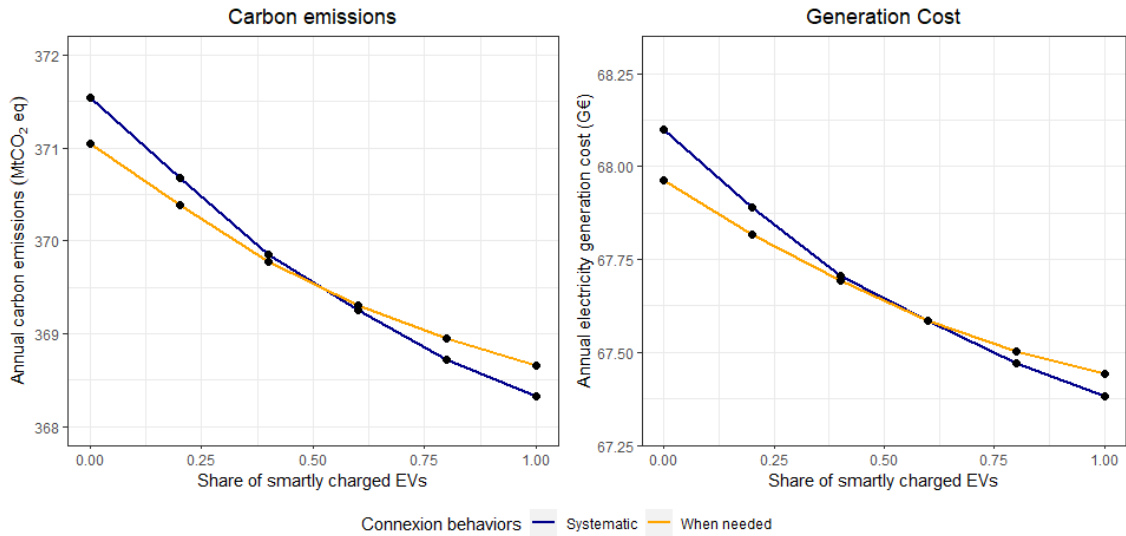


Figure 4.4: Impact of EV smart charging (unidirectional and at daily scale) adoption on pan-European electricity generation operational costs and emissions

Daily or weekly flexibility

As identified in section 4.2.3, EVs are often studied as flexibility providers at the daily scale, though increasing BEV battery capacities imply that their charge can be delayed by a few days without any drawbacks on the mobility needs side. In this section, we compare three scenarios to evaluate EV flexibility potential at the daily and weekly time-scales. The first scenario is the uncontrolled charge of EVs that connect every time they get to a charging point. In the second scenario, every EV adopts smart charging, at the daily scale (i.e. the battery is always fully charged when the vehicle leaves). In the third scenario, every EV is in weekly smart charging mode (i.e. the battery is always kept at least at 30% SOC, but not necessarily charged every day).

For the analysis in Figure 4.5, a specific week has been selected (late-October of a given weather year), which includes two days with medium renewable generation followed by three days with high wind production, and then at the end of the week low renewable generation, followed again by two days with high wind production. With uncontrolled charging, a large share of EV demand is synchronous with peak demand and comes after solar generation times, which means that thermal power plants and imports are required to match demand at peak times.

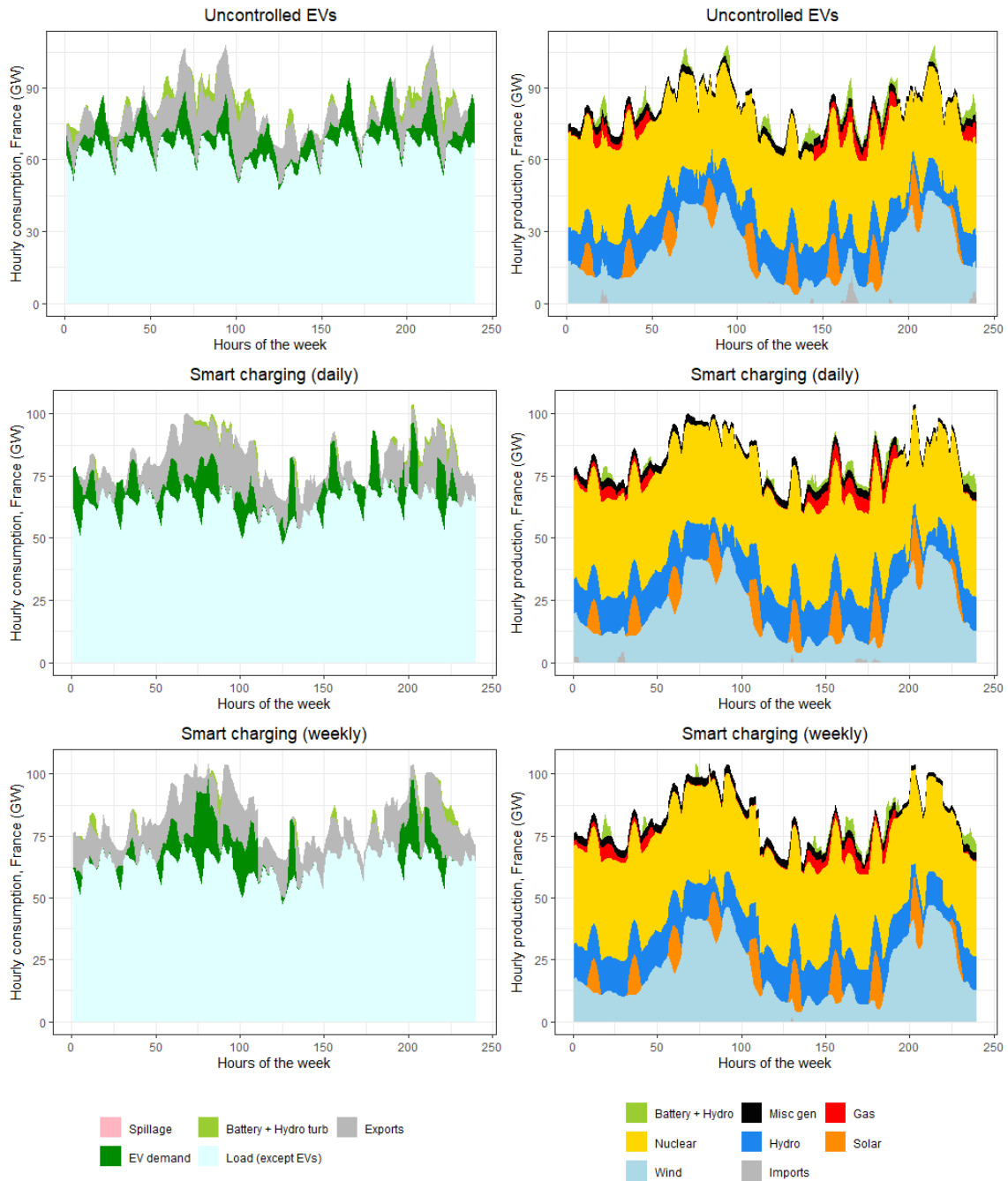


Figure 4.5: French electricity hourly demand and generation per technology for a selected week in October, for the no flexibility, daily flexibility and weekly flexibility scenarios

Second, the scenario with daily EV flexibility shows that with smart charging, EVs are charged as much as possible in peak times that coincide with solar generation, and thus less electricity is imported or generated with gas power plants. Lastly, in the weekly flexibility scenario, EVs avoid charging in times that coincide with low renewable (especially wind) energy production, which further reduces

imports, gas generation and renewable spillage compared to other scenarios. The gains for daily and weekly flexibility of EV charging are not similar for every week in the year, as longer periods of low-renewable generation do not allow weekly flexibility to reduce emissions and cost as much as in the time period selected for Figure 4.5.

In practice, such a weekly EV demand optimization could turn out less efficient, due to imperfect forecasting of supply and demand.

Time-of-use charging

In this section, we compare three time-of-use charging approaches. First, a basic control signal, where the charging of each vehicle connecting at peak demand (18:00–21:00) is postponed by three hours. Second, an improved tariff profile at the daily level, calculated from an average smart charging profile over 4 types of day: summer weekday, summer weekend, winter weekday, and winter weekend. Finally, improving tariff profiles at the weekly level, where the profile is averaged for 7-day long load curve results of a smart charging (weekly flexibility) simulation.

Simple controls through time-of-use tariffs can reduce the operating cost of the system compared to an uncontrolled scenario. Flexibility is substantially greater if a more optimal tariff profile is used. On the other hand, the weekly-built tariffs do not bring significant gain in the profile construction, since weekly flexibility is mainly useful for dynamically adapting to days where renewable generation is low.

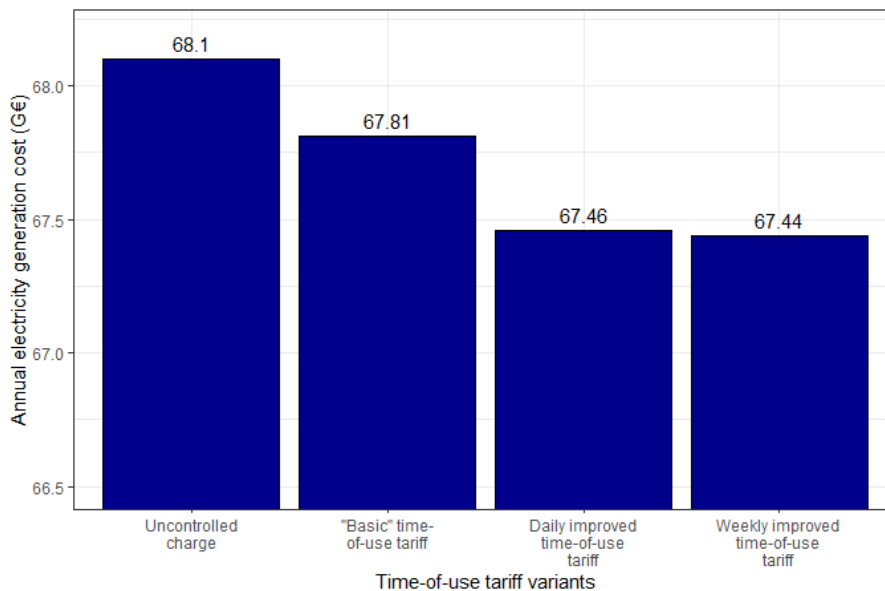


Figure 4.6: Comparison of time-of-use strategies on annual European electricity generation cost (for EV flexibility in France only, and every EV in systematic connection behavior)

Vehicle-to-grid

Different degrees of V2G adoption were also simulated, for two main options: with a limit of one additional battery cycle per week, or without any injection limit (in relation to the constraint 4.11 of our methodology). In our simulations, PHEVs are not available for V2G, due to their limited battery capacity. In both cases, but especially in the scenario with no injection limit, the more V2G is developed, the lower the marginal gain of adding V2G flexibility to the electric system (Figure 4.7, where V2G is compared with daily smart charging). The additional gains of adding V2G is nearly decreasing at every 5% increment in our simulation. This result also implies that in a electrical system with a lack of flexibility, V2G could be 3 to 4 times more profitable for the user than in a system with sufficient flexibility.

In practice, bidirectional charging is currently growing mainly for frequency regulation markets (Borne et al., 2018), but we identify here a potential on energy markets in a scenario with high adoption of renewables, where the injection of the energy stored in the battery (either to power the house via V2H, or directly on the grid) has economic and environmental benefits.

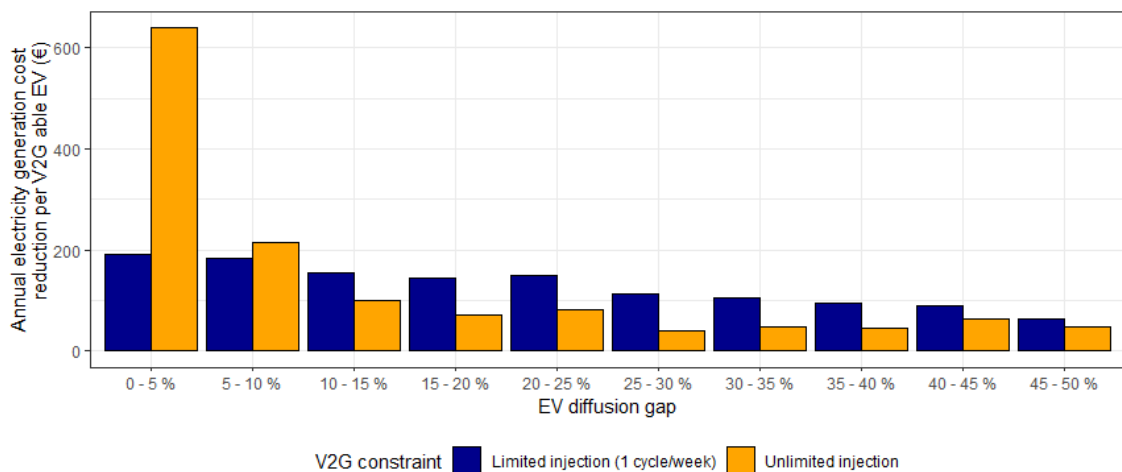


Figure 4.7: Incremental effect of V2G adoption (EV flexibility in France, operational cost variation at the European scale), all remaining EVs in unidirectional smart charging

Comparison of those strategies

Once all smart charging modes have been described and analyzed, we graphed Figure 4.8 to compare them. It appears that all control modes significantly reduce the total operational cost of the European power system by 0.4% to 1.8%. The gains with time-of-use tariff charging are clearly increased by using an improved tariff signals than a basic 2 hours shift. Finally, for the most efficient solutions (dynamic smart charging and V2G), weekly flexibility adds a significant gain in a scenario with a high share of solar and wind generation, which increases the need

for such flexibility.

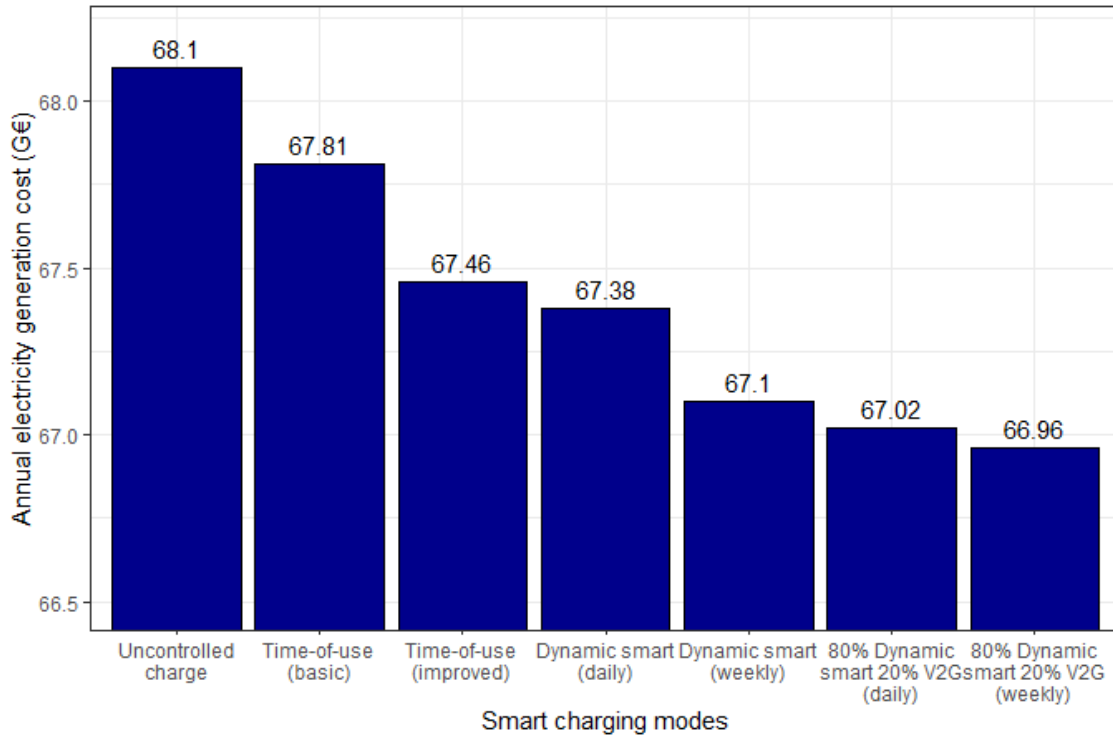


Figure 4.8: Annual European electricity generation operational costs for each charging strategy (for EV flexibility in France only, and every EV in systematic connection behavior)

Finally, the distribution of hourly electricity generation costs (sorted in ascending order) for the main smart charging modes studied in this Chapter are presented in Figure 4.9. The distribution for improved time-of-use tariff and dynamic smart charging are very close and overlapping in this graph. This graph illustrates as well that our simulation optimizes the electricity generation system as a whole, and does not model explicitly a given market (day-ahead for instance), which means that it is not possible to observe and study negatives prices here. However, negative prices may appear under some circumstances, when taking into account competition between actors and negative price bidding to keep a power plant running.

Here we highlight the impacts of smart charging modes on marginal generation costs, showing that increasing demand-side flexibility has two effects: it reduces the frequency of negative or near-zero marginal costs (when all consumption is covered by renewables excluding hydro storage) and decreases the occurrence of very high marginal costs, as EVs withdraw less electricity (or even inject electricity into the grid) during peak demand when they are smartly-charged. We also add for comparison purposes the distribution of generation costs without EV demand (and the same generation capacities), which is not realistic, but illustrates

the approximation of studying large EV diffusion from historical market data (without EVs).

This graph is generated in the base case scenario on thermal units marginal generation costs (see next subsection), which means that we can expect much higher peak prices in scenarios with much higher gas and oil prices.

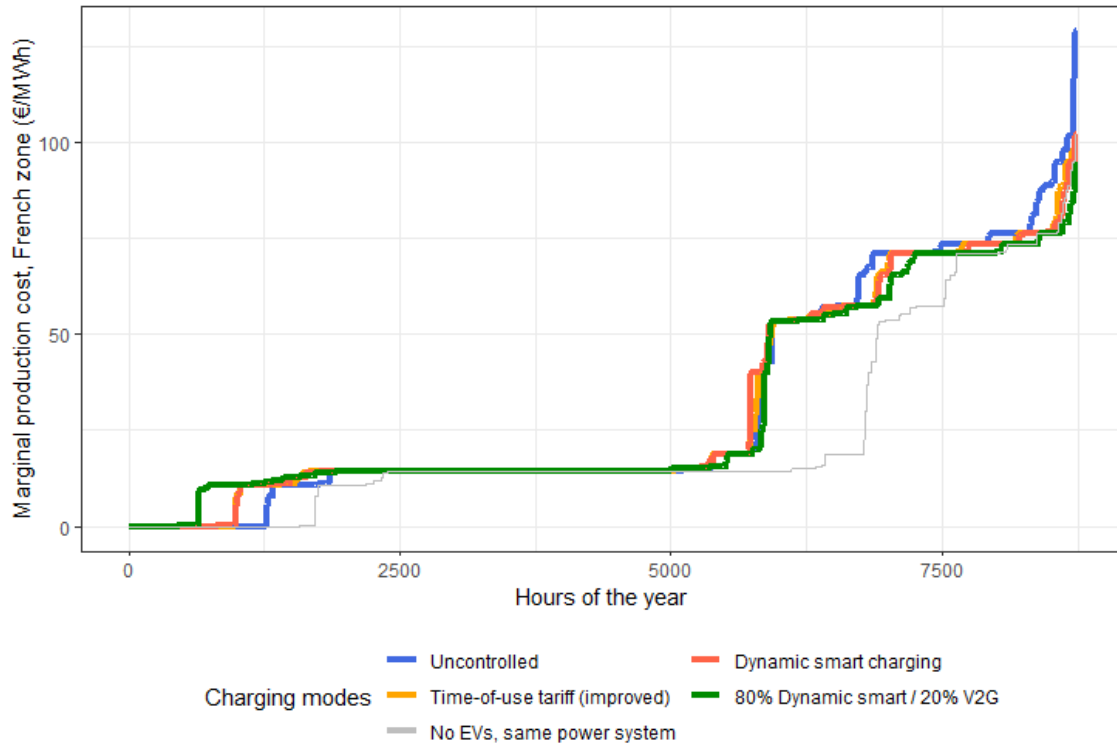


Figure 4.9: Price duration curves (distribution of electricity system marginal generation costs)

Impact of fuel prices on value of smart charging

All the results shown above were output from the initial electricity generation data from the 2020 TYNDP. In this input dataset and as often predicted in 2019, the average European marginal cost of electricity generation via gas power plants (including a mix of combined cycle and open cycle gas turbines, some with carbon capture and storage) for prospective studies is around 90€/MWh. Recent events show that gas can reach significantly higher prices for various reasons, including carbon tax increases, pandemics, and geopolitical conflicts.

Therefore, we evaluated the sensitivity of EV flexibility under several costs of electricity generation from gas power plants. This initial assumption of 90€/MWh cost of generated electricity from gas power plants corresponds to approximately 30€/MWh on the gas spot market (depending on efficiency of the plant and carbon taxes). Recently, gas prices skyrocketed from below 20 €/MWh in 2020 to over 100 €/MWh in Western Europe in early 2022 (Kuik et al., 2022). Hence, we compared

here EV smart charging results with up to 150 €/MWh gas market price (equivalent to around 315 €/MWh marginal cost of electricity generated from gas power plants).

Results in Figure 4.10 show that both the total European electricity generation OPEX and the gain from smart charging 24 million EVs are highly dependent on gas prices. This finding implies that absolute values for generation cost reduction and EV owner flexibility revenue when studying EV flexibility are to be taken with caution, under the set of assumptions used to compute them. The value of smart charging EVs increase along fossil fuel prices (as smart charging helps decreasing their use). However, the relative ranking of EV charging flexibility modes, and other indicators such as carbon emissions and renewable energy spillage, are less sensitive to fuel price.

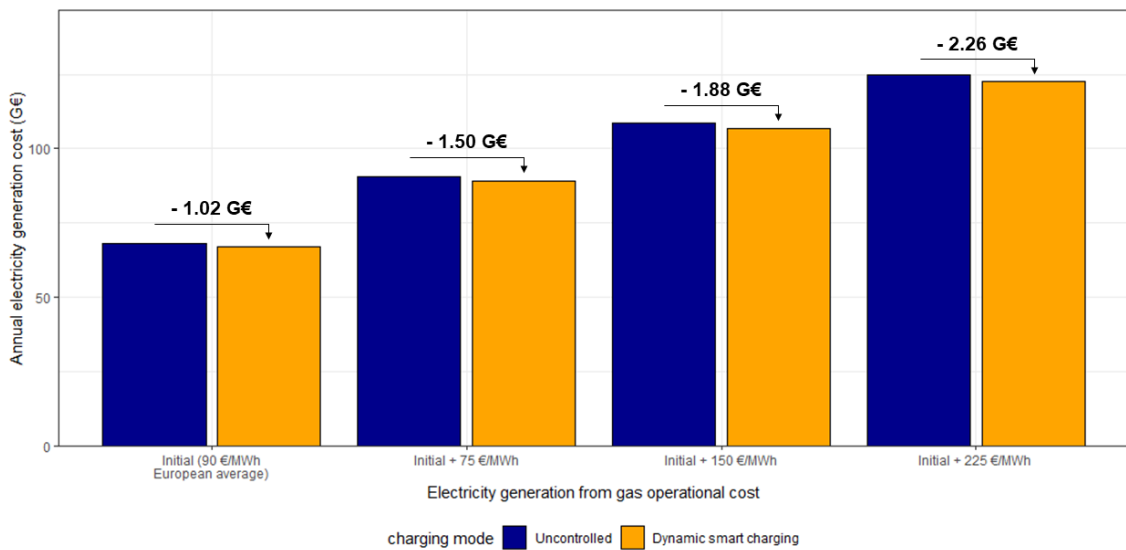


Figure 4.10: Impact of marginal costs for gas power plants on EV smart charging benefits for the European electricity system. For comparison purposes, 100% EVs in uncontrolled charging mode (blue) and dynamic smart charging (orange)

Others

In the appendix 4.A, we illustrate some other sensitivity studies, especially on battery capacity, charging point power, other demand-side flexibility means, lower frequency of mid-day connection. These parameters have lesser impact on EV demand-side flexibility than what is presented in this section 4.3. The results for other indicators than costs and emissions at the European level are shown, as well as the results per weather year.

4.4 Discussion

EVs can be smartly charged via various different strategies that respond to several challenges the electrical system is set to face with growing market penetration of renewable energy sources. In this Chapter, we focused on optimal hourly operation of the European power system (generating units, storage, interconnection). The smart charging modes suited to each flexibility challenge, as well as the additional equipment required, are summarized in Table 4.4.

In France, in 2021, only 37% of EV owners had already adopted smart charging options, and among them more than 75% are in basic delayed charging (Enedis, 2020), so the potential for further developing EV flexibility is still huge.

To simplify the analysis, we studied extreme cases with 100% EVs in one smart charging mode, but in practice these options will coexist, depending on how far EV owners accept each charging mode. It would be instructive to simulate these different modes in competition to see how they interact with each other. This kind a simulation would also serve to compare the benefits of each solution by considering the total cost of infrastructure (charging stations and communication devices) and the cost of additional battery degradation from V2G. Moreover, we carried out our study in a given electricity generation system, but the scaling of flexibility solutions and the investment in generation capacities may depend on political choices surrounding demand-side flexibility development (including EVs).

Nevertheless, the methodology for calculating the availability of vehicles at charging stations and the constraint on EV charging requires setting arbitrary values for the minimum SOC to be maintained, and the limits of V2G injection. This parameters would be refined or confirmed once more feedback on EV smart charging is available. Additionnaly, the mode of EV aggregation into a single object is also an approximation, but no perfect method has been found in the literature, and we tried here to improve the existing literature by adding limitation on energy withdrawn in several time windows, computed from our mobility model.

Finally, the analysis of the results in this work is done solely from the point of view of the electrical system. The issue of how to incentivize EV users to adopt smart charging behaviors is not addressed, while some authors highlight that market rules are not currently ready to maximize EV flexibility (Borne et al., 2018; Codani et al., 2015). It is important to point out that though the "systematic connection" behavior is highly beneficial for the power system, the cost difference perceived by the consumer may be too small to incentivize such a behavior.

Electrical system hourly dispatch challenges in 2040	Uncontrolled EV charging	Time-of-use tariff charging	Dynamic smart charging (daily)	Dynamic smart charging (weekly)	V2G (daily)	V2G (weekly)
Avoiding a larger peak demand (18:00–20:00)	No	Yes	Yes	Yes	Yes	Yes
Better synchronize EV charging with peak solar production	No	Depends on tariff structure	Yes	Yes	Yes	Yes
Adapt dynamically to daily variations in renewable generation (especially wind)	No	No	Yes	Yes	Yes (added value of V2G)	Yes (added value of V2G)
Adapt to weekly variations in renewable generation (especially wind)	No	No	No	Yes	Partially	Yes
Most suited connection behavior	Any, preferably <i>when convenient</i>	Any, preferably <i>systematic</i>	Preferably <i>systematic</i>	<i>Systematic</i> connection only	Preferably <i>systematic</i>	<i>Systematic</i> connection only
Additional charging and communication equipment required	None	Smart-meter	Smart communication	Smart communication	Smart communication and V2G charger	Smart communication and V2G charger

Table 4.4: Main challenges for the electricity system hourly supply-demand adequacy and appropriate EV smart charging modes

4.5 Conclusion

To analyze the impacts of EV smart charging adoption on power systems, we propose a two-step methodology. Firstly, EV connection and demand data for various connection behaviors and EV development scenarios are generated from a mobility model based on travel survey data (see Chapter 3). Secondly, these datasets are integrated into a power system supply–demand adequacy model to estimate

the value of EV smart charging for the European electrical system and compare a large number of smart charging strategies. For prospective studies on EV flexibility, we strongly advocate co-modeling the transport sector with the electricity sector to go further than most previous work in the literature.

The cost and carbon emissions reduction of the unidirectional smart charging of 24 Million EVs in France (compared to uncontrolled charge) is estimated at around 1.1 G€ and 3.2 MtCO₂-eq annually, under our initial assumptions. IEA (2019) reviews life-cycle analysis comparisons between EVs and thermal vehicles. On average, in a low carbon electricity generation power system, life cycle (over 10 years) total emissions of an EV (400 km range) are estimated at around 14 tCO₂-eq, compared to 34 tCO₂-eq for a thermal vehicle. Thus, each EV reduces emissions by around 2 tCO₂-eq per year, compared to the same distances being travelled with a thermal vehicle. As a result, in our scenario with 24 Million EVs in France, we can expect a 48 GtCO₂-eq yearly reduction of emissions of EV compared to thermal vehicles, additionally to the 3.2 MtCO₂-eq reduction of electricity generation emissions from smart charging. We can conclude from this analysis, that 6.5% of the carbon emissions reduction of a smartly charged EV is linked to the electricity generation sector in our scenario, with an electricity generation sector already low-carbon. Higher shares of carbon reduction linked to the electricity generation sector are forecasted for areas in the world with high carbon intensive electricity generation.

We identified in this Chapter three major recommendations to get the maximum value from EV demand flexibility. First, tariff-based, dynamic smart and V2G charging modes should be developed, depending on user acceptance of these technologies. Second, it seems important to incentivize mid-day charging, especially with charging stations at the workplace for daily commuters or at home for prosumers, to better synchronize charging with peak solar production. Lastly, EV flexibility is maximized by encouraging systematic connection, to enlarge the accessible charging window and even allow EV charging to be postponed to following days (weekly flexibility).

For prospective studies that premise large EV adoption, we advise using electricity-system models, as increasing demand-side flexibility influences market prices, hence making the price-taker assumption a dangerous one, with significant impact on results. The benefits of converting an EV to smart charging are not linear, especially with V2G that may meet flexibility needs even with limited adoption. The value of smart charging is also highly dependent on parameters that are exogenous from the transport sector, such as gas prices and carbon tax. Additionally, the competition with other prospective demand-side flexibility sources, especially hydrogen electrolyzers and industrial load management is worth studying.

To go further with the analysis of EV flexibility, this work may be complemented by studying other potential EV flexibility–electricity system interactions than hourly supply–demand dispatch, such as network congestion (at the transmission and distribution level), frequency regulation, and intra-day energy mar-

kets studied with imperfect forecasts. These topics may not be conflicting with each others in terms of EV flexibility (e.g. for prosumers, charging EV at peak solar production reduces both electricity generation costs and grid congestion). Furthermore, our study focuses only on personal vehicles, whereas other means of mobility are also expected to 'go electric', such as two-wheelers, trucks, and buses, which could bring additional electricity flexibility potential from the transport sector, as well as fuel-cell vehicles powered by electrolyzer-produced hydrogen. Finally, further work based on these results, such as complementary evaluations on other countries, other mobility solutions and other electricity generation scenarios should help design solutions to incentivize and further develop EV demand flexibility. ¹

¹The main findings of this Chapter, along with a short summary of Chapter 3 have been published in Lauvergne et al. (2022)

Bibliography

- AntaresSimulator. (2022). <https://antares-simulator.org/pages/software-presentation/1/>
- Arvesen, A., Völler, S., Hung, C. R., Krey, V., Korpås, M., & Strømman, A. H. (2021). Emissions of electric vehicle charging in future scenarios: The effects of time of charging. *Journal of Industrial Ecology*, 25(5), 1250–1263. <https://doi.org/10.1111/jiec.13144>
- Barot, S., & Taylor, J. A. (2017). A concise, approximate representation of a collection of loads described by polytopes. *International Journal of Electrical Power & Energy Systems*, 84, 55–63. <https://doi.org/10.1016/j.ijepes.2016.05.001>
- Borne, O., Perez, Y., & Petit, M. (2018). Market integration or bids granularity to enhance flexibility provision by batteries of electric vehicles. *Energy Policy*, 119, 140–148. <https://doi.org/10.1016/j.enpol.2018.04.019>
- Borozan, S., Giannelos, S., & Strbac, G. (2021). Strategic Network Expansion Planning with Electric Vehicle Smart Charging Concepts as Investment Options. *Advances in Applied Energy*, 100077. <https://doi.org/10.1016/j.adapen.2021.100077>
- Cai, H., Chen, Q., Guan, Z., & Huang, J. (2018). Day-ahead optimal charging/discharging scheduling for electric vehicles in microgrids. *Protection and Control of Modern Power Systems*, 3(1), 9. <https://doi.org/10.1186/s41601-018-0083-3>
- Codani, P., Petit, M., & Perez, Y. (2015). Participation of an electric vehicle fleet to primary frequency control in France. *International Journal of Electric and Hybrid Vehicles*, 7(3), 233. <https://doi.org/10.1504/IJEHV.2015.071639>
- Doquet, M., Fourment, C., & Roudergues, J. (2011). Generation & transmission adequacy of large interconnected power systems: A contribution to the renewal of Monte-Carlo approaches. *2011 IEEE Trondheim PowerTech*, 1–6. <https://doi.org/10.1109/PTC.2011.6019444>
- Enedis. (2020). Enquête comportementale auprès des possesseurs de véhicules électriques : Habitudes de roulage et de recharge.
- ENTSO-E. (2020a). Completing the map – Power system needs in 2030 and 2040, 70.
- ENTSO-E. (2020b). Ten-year network development plan (tyndp) 2020, consultation, last accessed in June 2022. <https://consultations.entsoe.eu/system-development/tyndp2020/>
- Fischer, D., Harbrecht, A., Surmann, A., & McKenna, R. (2019). Electric vehicles' impacts on residential electric local profiles – A stochastic modelling approach considering socio-economic, behavioural and spatial factors. *Applied Energy*, 233–234, 644–658. <https://doi.org/10.1016/j.apenergy.2018.10.010>
- Foley, A., Ó Gallachóir, B., Hur, J., Baldick, R., & McKeogh, E. (2010). A strategic review of electricity systems models. *Energy*, 35(12), 4522–4530. <https://doi.org/10.1016/j.energy.2010.03.057>

- Funke, S. Á., Plötz, P., & Wietschel, M. (2019). Invest in fast-charging infrastructure or in longer battery ranges? A cost-efficiency comparison for Germany. *Applied Energy*, 235, 888–899. <https://doi.org/10.1016/j.apenergy.2018.10.134>
- Green, R. C., Wang, L., & Alam, M. (2011). The impact of plug-in hybrid electric vehicles on distribution networks: A review and outlook. *Renewable and Sustainable Energy Reviews*, 15(1), 544–553. <https://doi.org/10.1016/j.rser.2010.08.015>
- Heggarty, T., Bourmaud, J.-Y., Girard, R., & Kariniotakis, G. (2020). Quantifying power system flexibility provision. *Applied Energy*, 279, 115852. <https://doi.org/10.1016/j.apenergy.2020.115852>
- IEA. (2019). *Global EV Outlook 2019: Scaling-up the transition to electric mobility*. OECD. <https://doi.org/10.1787/35fb60bd-en>
- Jarvis, R., & Moses, P. (2019). Smart Grid Congestion Caused by Plug-in Electric Vehicle Charging. *2019 IEEE Texas Power and Energy Conference (TPEC)*, 1–5. <https://doi.org/10.1109/TPEC.2019.8662152>
- Kuik, F., Adolfsen, J., Lis, E., & Meyler, A. (2022). Energy price developments in and out of the covid-19 pandemic – from commodity prices to consumer prices. https://www.ecb.europa.eu/pub/economic-bulletin/articles/2022/html/ecb.ebart202204_01~7b32d31b29.en.html
- Lauvergne, R., Perez, Y., Françon, M., & Cruz, A. T. D. L. (2022). Integration of electric vehicles into transmission grids: A case study on generation adequacy in Europe in 2040. *Applied Energy*, 326, 120030. <https://doi.org/https://doi.org/10.1016/j.apenergy.2022.120030>
- Li, R., Wang, Z., Gu, C., Li, F., & Wu, H. (2016). A novel time-of-use tariff design based on gaussian mixture model. *Applied Energy*, 162, 1530–1536. <https://doi.org/https://doi.org/10.1016/j.apenergy.2015.02.063>
- Liu, Z., Wu, Q., Nielsen, A., & Wang, Y. (2014). Day-Ahead Energy Planning with 100% Electric Vehicle Penetration in the Nordic Region by 2050. *Energies*, 7(3), 1733–1749. <https://doi.org/10.3390/en7031733>
- Mehta, R., Verma, P., Srinivasan, D., & Yang, J. (2019). Double-layered intelligent energy management for optimal integration of plug-in electric vehicles into distribution systems. *Applied Energy*, 233-234, 146–155. <https://doi.org/10.1016/j.apenergy.2018.10.008>
- Pelletier, S., Jabali, O., Laporte, G., & Veneroni, M. (2017). Battery degradation and behaviour for electric vehicles: Review and numerical analyses of several models. *Transportation Research Part B: Methodological*, 103, 158–187. <https://doi.org/10.1016/j.trb.2017.01.020>
- Ried, S., Dengiz, T., Soldner, S., & Jochem, P. (2020). Aggregating load shifting potentials of electric vehicles for energy system models. *2020 17th International Conference on the European Energy Market (EEM)*, 1–6. <https://doi.org/10.1109/EEM49802.2020.9221974>
- Robinius, M., Otto, A., Syranidis, K., Ryberg, D. S., Heuser, P., Welder, L., Grube, T., Markewitz, P., Tietze, V., & Stolten, D. (2017). Linking the Power and Transport Sectors—Part 2: Modelling a Sector Coupling Scenario for Germany. *Energies*, 10(7), 957. <https://doi.org/10.3390/en10070957>

- RTE. (2019). Integration of electric vehicles into the power system in France.
- Schill, W.-P., & Gerbaulet, C. (2015). Power system impacts of electric vehicles in Germany: Charging with coal or renewables? *Applied Energy*, 156, 185–196. <https://doi.org/10.1016/j.apenergy.2015.07.012>
- Slednev, V., Jochem, P., & Fichtner, W. (2021). Impacts of electric vehicles on the European high and extra high voltage power grid. *Journal of Industrial Ecology*, jiec.13216. <https://doi.org/10.1111/jiec.13216>
- Soares, F., Lopes, J. A., Almeida, P., Moreira, C., & Seca, L. (2011). A stochastic model to simulate electric vehicles motion and quantify the energy required from the grid. *Power Systems Computation Conference (PSCC)*.
- Wang, Z., Jochem, P., Yilmaz, H. Ü., & Xu, L. (2021). Integrating vehicle-to-grid technology into energy system models: Novel methods and their impact on greenhouse gas emissions. *Journal of Industrial Ecology*, jiec.13200. <https://doi.org/10.1111/jiec.13200>
- Wolinetz, M., Aksen, J., Peters, J., & Crawford, C. (2018). Simulating the value of electric-vehicle-grid integration using a behaviourally realistic model. *Nature Energy*, 3(2), 132–139. <https://doi.org/10.1038/s41560-017-0077-9>
- Wu, F., & Sioshansi, R. (2017). A two-stage stochastic optimization model for scheduling electric vehicle charging loads to relieve distribution-system constraints. *Transportation Research Part B: Methodological*, 102, 55–82. <https://doi.org/10.1016/j.trb.2017.05.002>
- Wulff, N., Steck, F., Gils, H. C., Hoyer-Klick, C., van den Adel, B., & Anderson, J. E. (2020). Comparing Power-System and User-Oriented Battery Electric Vehicle Charging Representation and Its Implications on Energy System Modeling. *Energies*, 13(5), 1093. <https://doi.org/10.3390/en13051093>
- Xydas, E., Marmaras, C., & Cipcigan, L. M. (2016). A multi-agent based scheduling algorithm for adaptive electric vehicles charging. *Applied Energy*, 177, 354–365. <https://doi.org/10.1016/j.apenergy.2016.05.034>

4.A Additional results and sensitivity studies

In this appendix are gathered additional results that complements the analysis of EV smart charging carried out in this Chapter.

Figure 4.11 illustrates the various indicators that can be chosen to compare smart charging scenarios in our case study, for the results of Figure 4.4. An additional result shown here is that EV smart charging in France has an impact on generation costs and carbon emissions in other European countries, which justify the choice of mostly illustrating results at the European scale in this Chapter.

Then in Figures 4.12 and 4.13, the 6 main smart charging modes compared in this Chapter are illustrated under another format: each dot corresponding to a time-step of our model (hourly), in graphs showing the correlation between EV demand and marginal generation cost (4.12) and average carbon emissions (4.13). It appears that for scenarios with 100% smart charging or V2G, EV demand is close to 0 at all time steps when marginal costs and emissions are the highest. Time-of-use tariffs achieve at reducing the frequency of simultaneously high EV demand and generation marginal cost, as on average our improved time-of-use profile matches the optimal charging times, but not as much as dynamic smart charging modes.

Figure 4.14 compares the flexibility value of EV smart charging with the stationary batteries installed in France for grid flexibility in our scenario (6 GW maximum power and 12 GWh total capacity in our scenario). These batteries are mainly used for daily flexibility and a little bit for weekly flexibility. It appears that the diffusion of smart charging from 20% to 40% EVs (which means 4.9 Million EVs in our scenario) produces slightly more flexibility than the initial stationary batteries of our scenario in this sensibility study.

Next, in Figure 4.15, we illustrate that the flexibility of other neighboring countries (which has not been modified in other sensitivity analysis on EV demand flexibility in France) also has a large impact on total European costs and thus on the value EVs can generate by proving demand-side flexibility. Ideally, the flexibility of EV demand should be modelled for each country in such simulation, but analyzing mobility patterns in each country is very time-consuming compared to its limited added value when studying sensibilities on EV smart charging in France.

Figures 4.16 and 4.17 show what are the impacts of reducing the average battery capacity and charging point rated power (respectively). First, for the battery capacity, we observe very little impact when every vehicle is charged at 100% at every charging session (daily flexibility), for the two charging behaviors illustrated. However, when EVs accept weekly flexibility, lower battery capacities reduce the gains from delaying EV demand, as EV need to be charge more frequently. Secondly, when every charging point maximum power is reduced to those of a standard residential slow charger (3.7 kW), the gains of EV smart charging are slightly reduced for every scenario illustrated here, as less EV demand can be concentrated at time steps when marginal costs are the lowest. It is to be noted that for

weekly flexibility, reducing charging power appears less damageable than reducing battery capacities.

In Figure 4.18, the initial results of EV smart charging are compared with cases with lower mid-day connection, which illustrates that the more EVs are available at the mid-day window (10:00-15:00), the more EVs can be charged at peak solar production, when generation costs are often the lower in our scenario with 12.5% of solar among electricity generation in France (and 15% across Europe).

Finally, Figure 4.19 shows the difference between the 35 climate data years used for this case study (all results shown previously were averaged over these 35 years). We illustrate here, than results on Annual French carbon emissions and electricity exports differ greatly from a weather year to another. However, as expected, the charging modes compared are always in the same order, and EV flexibility greatly helps reducing electricity generation costs and emissions even in the most favorable weather year in our case study.

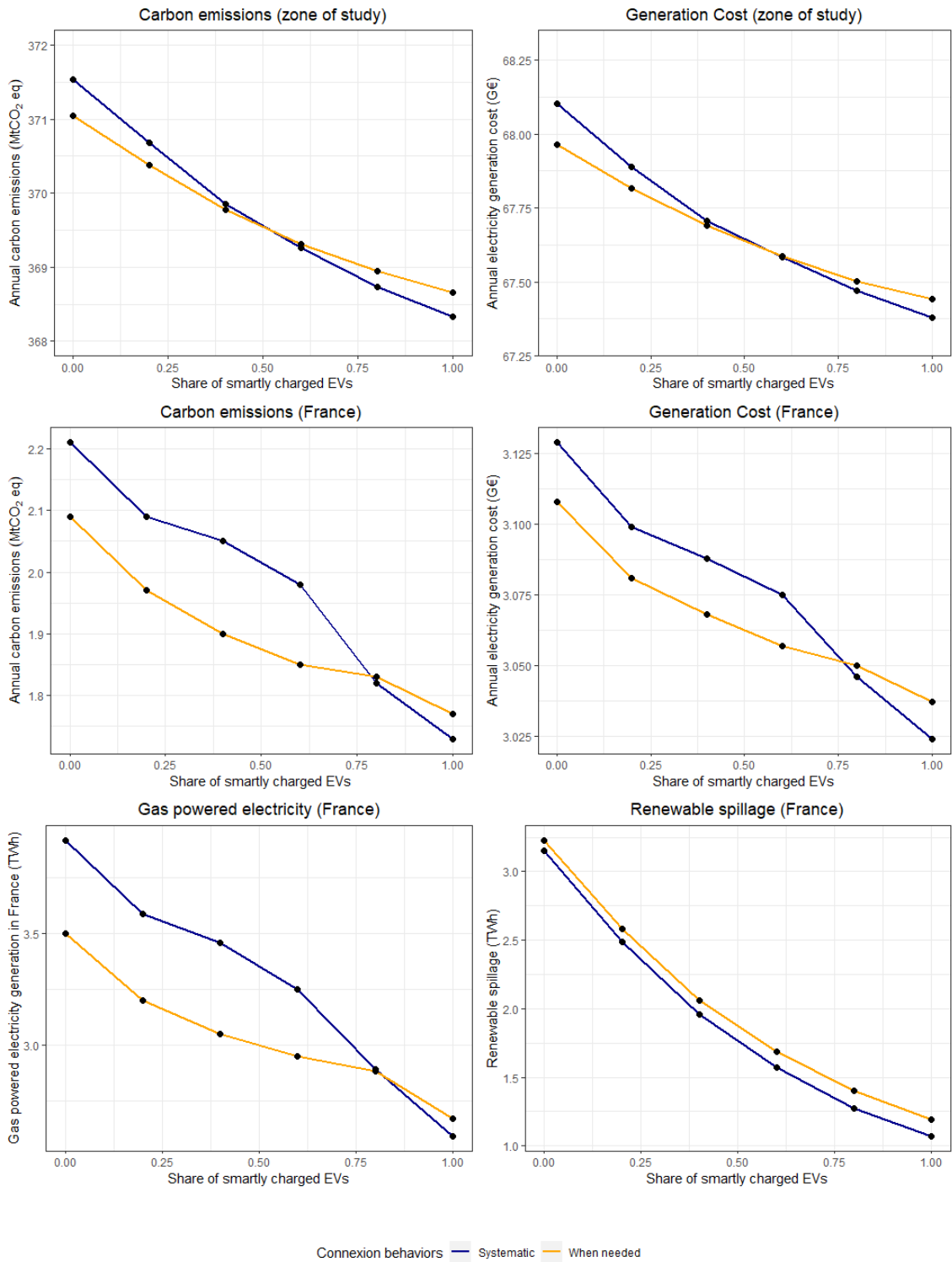


Figure 4.11: Comparison of 6 main indicators for the study of smart charging diffusion

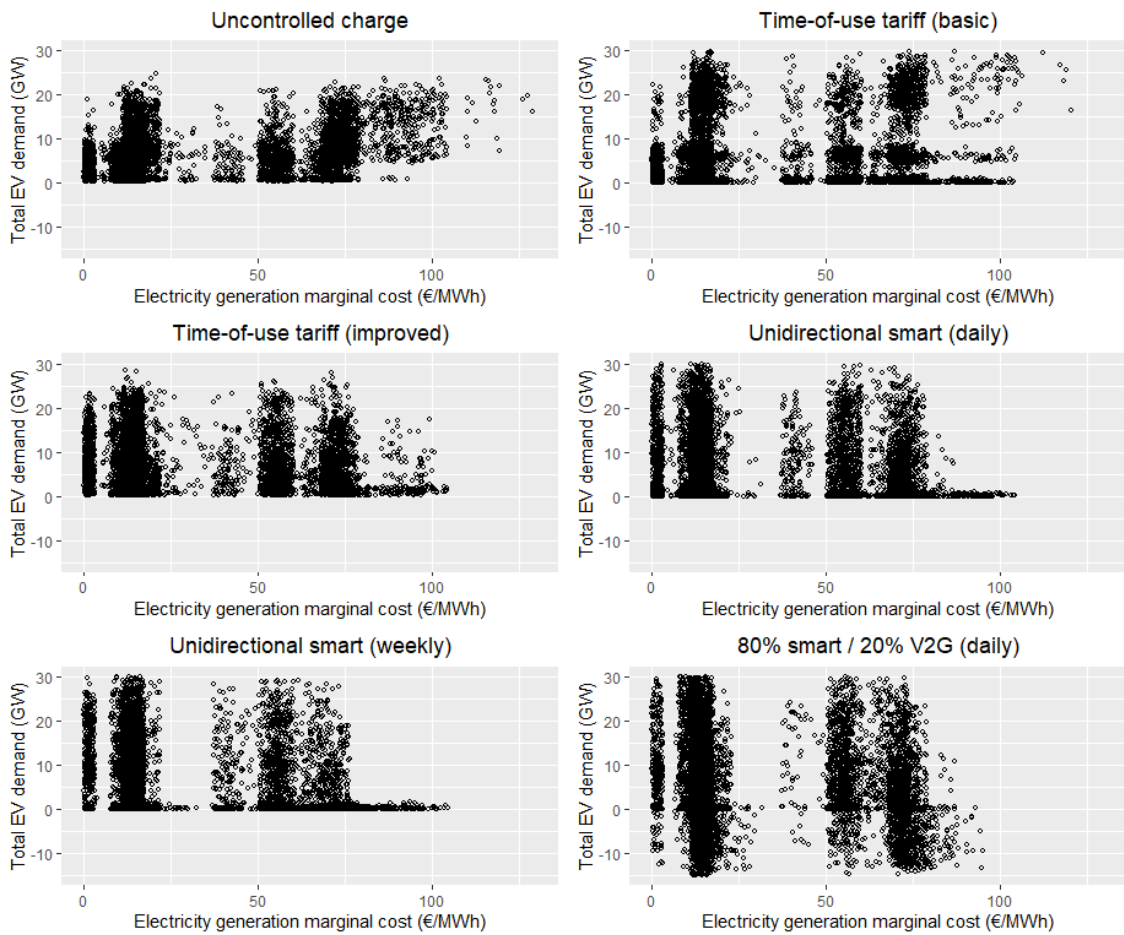


Figure 4.12: Comparison of the 6 smart charging variants described in Chapter 4, on the correlation between EV demand and hourly electricity generation marginal cost (± 3 €/MWh noise added for better readability)

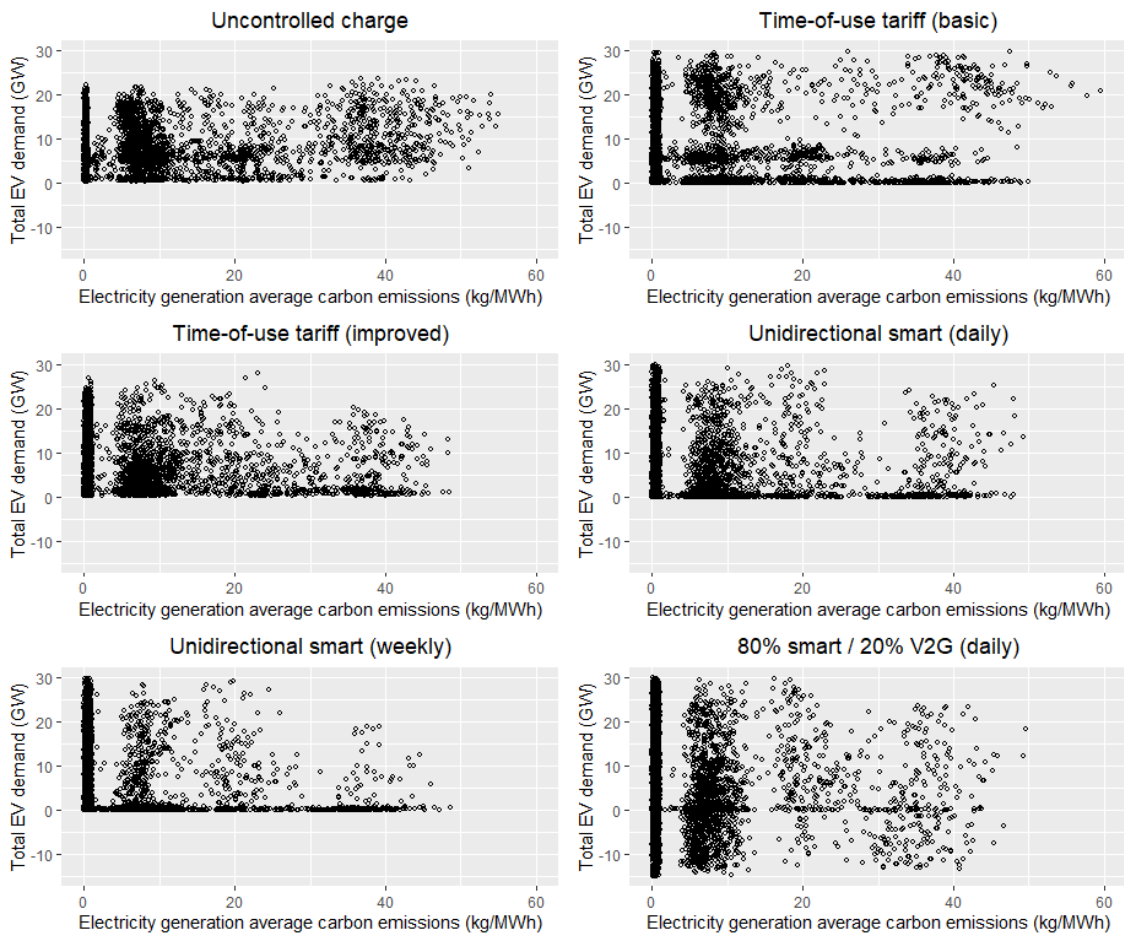


Figure 4.13: Comparison of the 6 smart charging variants described in Chapter 4, on the correlation between EV demand and electricity generation average carbon emissions

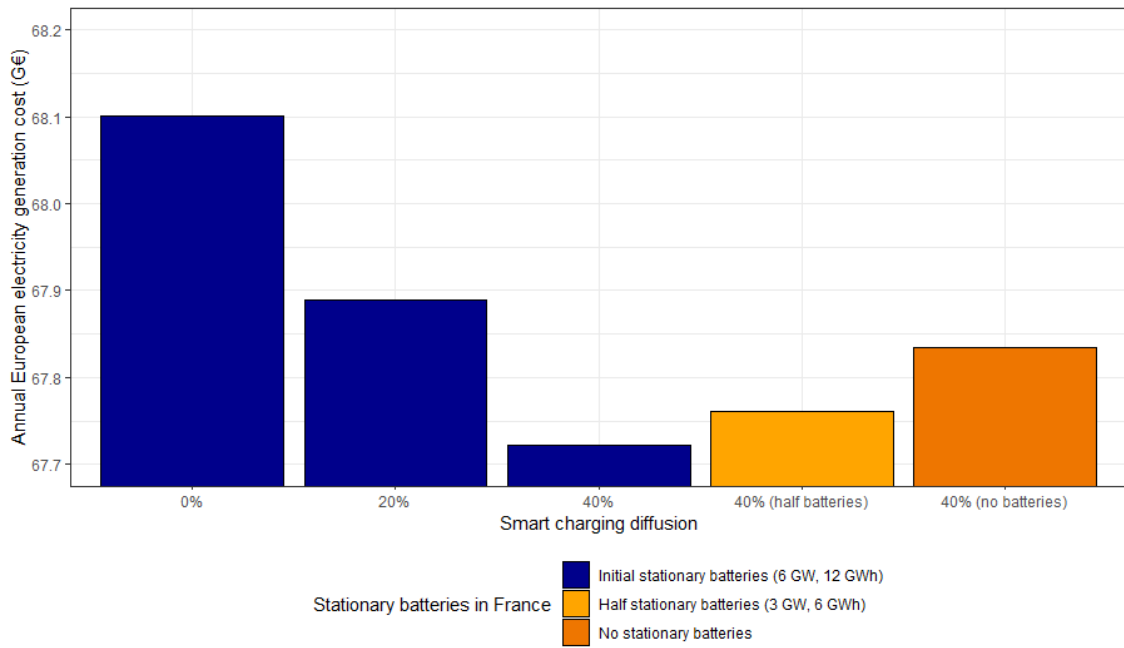


Figure 4.14: Comparison of smart charging diffusion and the use of stationary batteries to reduce European system operational costs (100% systematic connection)

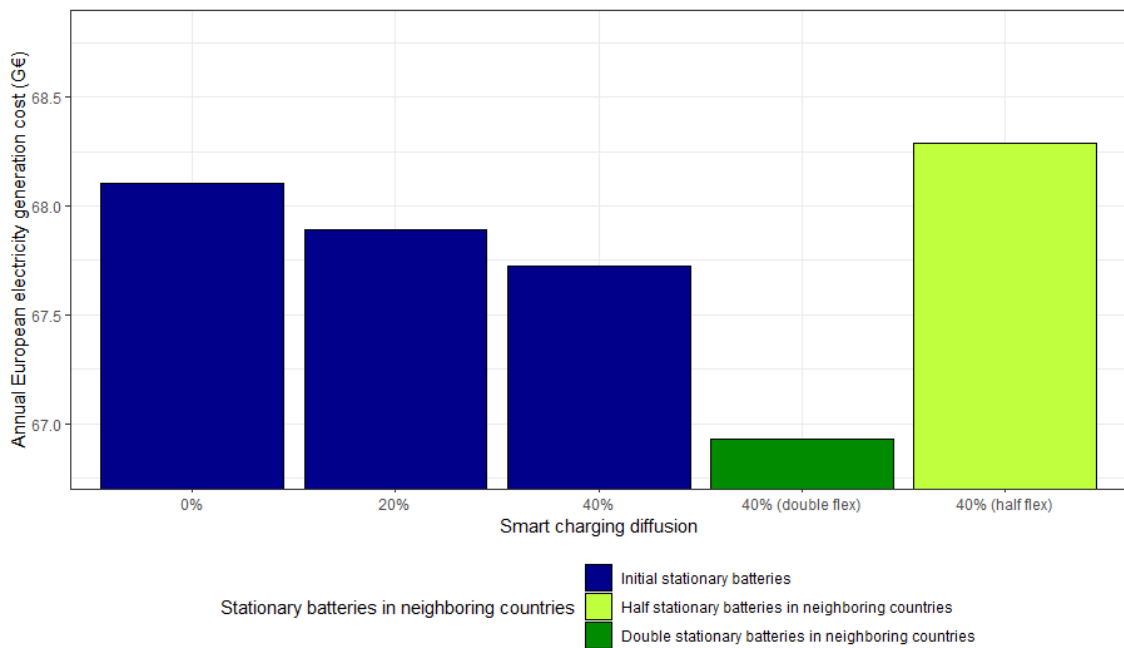


Figure 4.15: Impacts on flexibility in other countries on the European system operational costs (100% systematic connection)

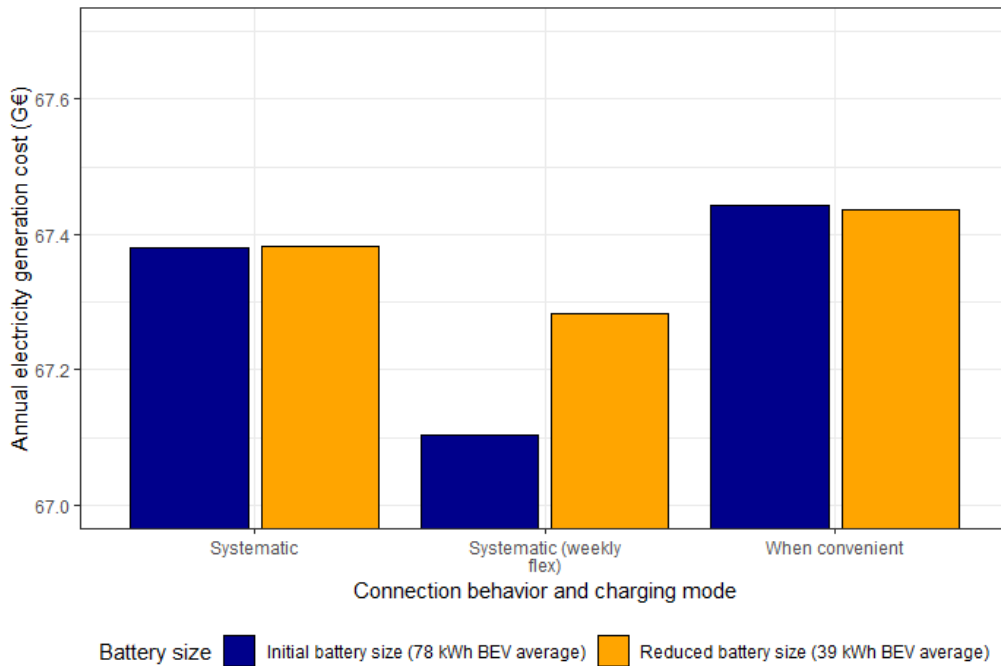


Figure 4.16: Impact of average EV battery capacity on demand side flexibility provided (100% smart charging diffusion)

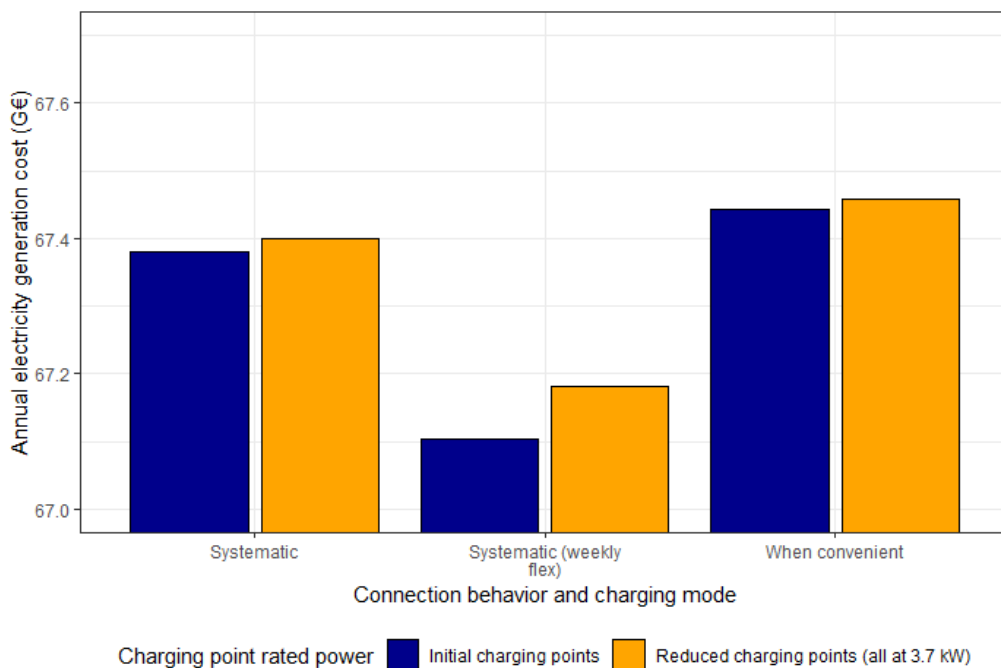


Figure 4.17: Impact of EV charging points rated power on demand side flexibility provided (average initial flexibility depends on connection behavior, 13.3 kW for systematic and 10.8 kW for when convenient) (100% smart charging diffusion)

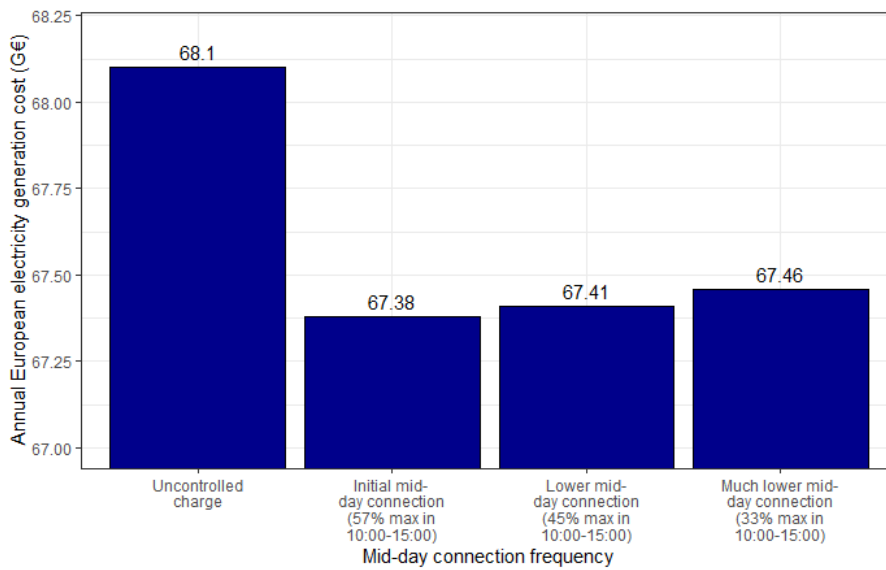


Figure 4.18: Impact of reduced mid-day EV connection on demand side flexibility provided

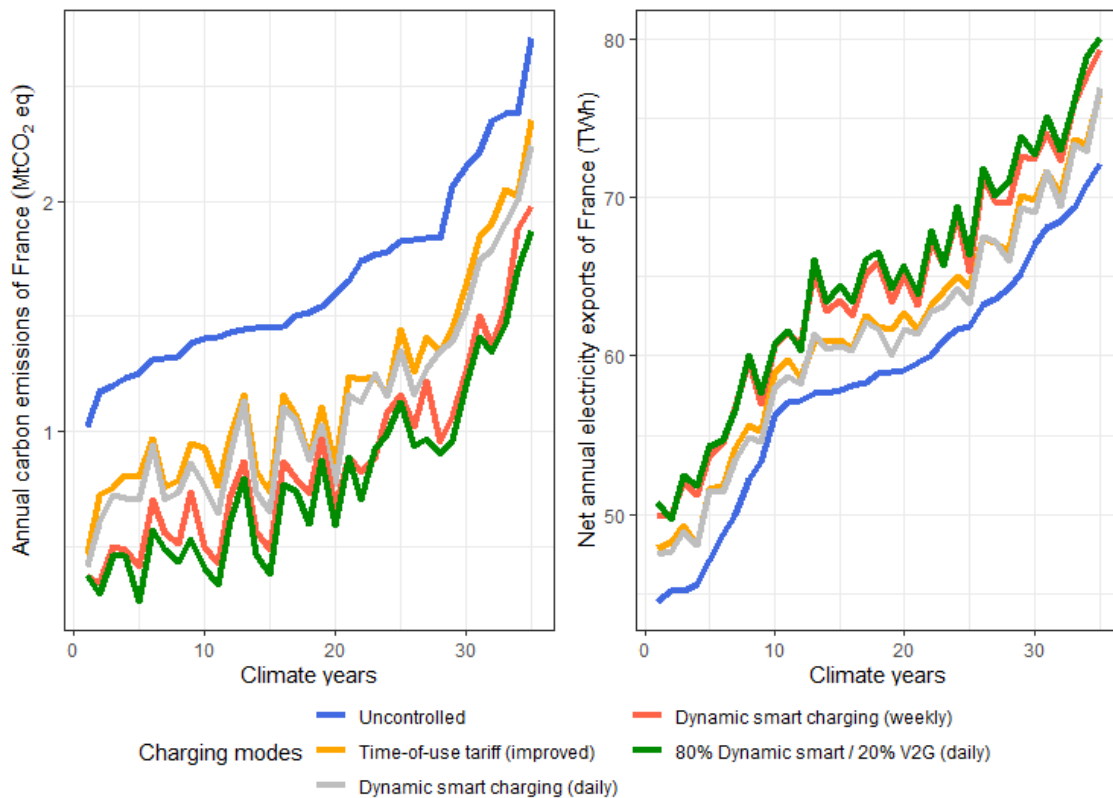


Figure 4.19: Influence of the weather year data on EV flexibility provision (sorting in ascending order for uncontrolled EV charge), for the smart charging modes compared in this Chapter

5 - General Conclusion

In this dissertation, we presented a methodological framework to study in a prospective horizon the different possibilities for electric vehicles to provide flexibility for the electrical systems, and illustrated them with case studies for the 2040 horizon, for the flexibility of French vehicles within the European electrical system.

This conclusive Chapter is composed of two parts. First, the main findings of this thesis are summarized. Then, the final section proposes several emerging research questions related to our work.

5.1 Summary of contributions

The **first introductory Chapter** of this dissertation describes the decarbonization perspectives of the transport and electricity generation sectors in the world and more particularly in Europe, in line with the Paris climate agreements and the EU Fit for 55 package. Electric vehicles appear as one of the main solutions to decarbonize the transport sector and reduce its related local pollution, on several means of transportation (individual cars, two-wheelers and heavy mobility), along with hydrogen and bio-fuels, by reducing the carbon intensity of energy. Urbanism change towards shorter distances to be travelled and modal shift towards public transport and soft mobility are solutions acting on other levers. Battery electric vehicles are especially efficient to reduce climate impacts of transport in areas where electricity generation is already low-carbon. On the other hand, the electrical system transition towards more renewable sources in the generation mix induce a decrease of the flexibility provided by generation units, which opens a potential value for expanding demand-side flexibility. Additionally, individual cars are likely to account for a significant share of the electricity demand-side flexibility related to mobility in the medium term (up to 2040).

It has already been proven that power grids can accommodate the expected EV diffusion in the short term (up to 2025) in most regions of the world, with low impacts on electricity markets, however, a major question still open is the impact of a broad EV development in the medium and long term.

Finally, we have listed the areas of interaction between electric mobility and the electric system, before selecting the core topic studied in the following Chapters.

Chapter 2 aims to compare modeling approaches for studying the integration of electric vehicles into different aspects of the power system. We show that although many studies in the literature focus mainly on the study of one of these two elements, a joint modeling of transportation and electrical system seems to be the most appropriate for prospective studies related to EV charging. We then observe that the various EV charging modeling approaches are adapted to dif-

ferent aspects of the electrical system, in particular activity-based models for very local studies, and aggregated statistical models based on mobility surveys for electricity dispatch studies without taking into account network issues.

Moreover, the evaluation of EV smart charging strategies is often based on historical data, assuming a price-taker hypothesis for EVs, which is relevant in the short term, but must be overcome for medium and long term prospective studies. For this purpose, several approaches and optimization objects can be found in the literature, which we have detailed.

We conclude the Chapter by proposing recommended approaches to address the different research questions mentioned in the introductory Chapter, and particularly the one studied in the following sections of this manuscript, for which a macro mobility model based on Monte-Carlo simulation of a travel survey dataset in order to generate averaged national charging patterns seems the most suited.

Chapter 3 presents the method chosen and developed for the generation of electric vehicle connection data from transport surveys. First, the main inputs and outputs of the model are described, as well as the 5 steps that compose the algorithm: generating the parameters of the vehicles, assigning trips to each vehicle, calculating the evolution of the consumption and location of these vehicles, deducing their connection times to the network (depending on the connection behavior). The vehicles' data are finally aggregated to generate a statistically representative charging profile for several socio-professional categories (commuters / retired, rural / urban) and trips (local mobility / long distance travels) that can be identified in our input data, in order to study multiple EV diffusion among the population scenarios.

This model is illustrated primarily to generate charging data from individual BEVs, but is also able of providing consumption data for PHEVs, FCEVs and other mobility segments, as long as similar data and assumptions are provided.

Beyond the uncontrolled electricity demand from the grid, our model also computes the evolution of the battery capacity and charging power connected to the grid, as well as the hourly amount of vehicles that disconnect (with their battery fully charged) and connect to the a charging point. All these data are needed to feed the EV smart charging module presented in Chapter 4.

Next, we illustrate for a case study at the 2040 time-horizon using the French national travel survey that the connection and demand of EVs depend on several assumptions, including the area of EV diffusion (longer distances and earlier arrival times are found in rural areas, compared with urban areas), the parameters of the charging infrastructure as well as the vehicle types (i.e. large BEVs, small BEVs, PHEVs), which the study of provides more accurate data than the use of a single averaged profile. The EV connection data generated shows that a significant share of uncontrolled EV demand is synchronous with electrical system peak demand (18:00-20:00), and two other smaller EV demand peaks are found, at the arrival at work (08:00-09:00) and at mid-day. Finally, as expected, the parameter that seems most key to the availability of vehicles for smart charging is

the frequency of connection to the grid , with a much wider window for optimal charging times in case of daily connection.











Chapter 4 concludes the methodological sequence presented in this thesis by modeling the multiple possibilities of EV smart charging, within AntaresSimulator, an economic dispatch model, which allows the study of the optimal EV charging periods (according to the charging constraints used to model the various smart charging approaches) that minimize the annual operational system costs.

Six main variants of EV smart charging are compared, ranking in the following ascending order for the reduction of cost and operational emissions of the electrical system: basic time-of-use tariffs, improved time-of-use tariffs, daily dynamic smart charging, weekly dynamic smart charging, V2G (daily) and V2G (weekly). Additionally, we perform several sensitivity analyses on these smart charging modes, including increasing gas prices, which has the largest impact on EV flexibility value among other sensitivity analyses. V2G is (as expected) the charging mode that reduces the most the electricity system emissions and generation costs. However, the more EVs are available for providing bidirectional flexibility, the less reduction of emissions and costs per EV are observed (as demand-side flexibility is more beneficial when the system lacks flexibility).

We observe different marginal production cost distributions according to the smart charging modes, which validates the initial hypothesis that EVs cannot be considered price-takers when their diffusion implies that their demand exceed a few percent of total electricity demand.

We then conclude this section by advising to develop these various smart charging modes concurrently (according to their acceptance by each consumer), while taking care to incentivize a frequent connection behavior, as well as to study in more detail the weekly flexibility of the recharge (when EVs are not fully charged at each charging session), enabled by the increasing volume of the battery capacity and relevant in a system with a high penetration of solar and wind production (that increase the need for weekly flexibility).

After highlighting the potential of EV demand-side flexibility and the major parameters that have an effect on its value for the hourly dispatch of the European electricity system, we summarise them in Figure 5.1, along with the current development of EV demand flexibility in France. Even if EV diffusion is still in its infancy, it appears clearly that more work is needed to incentivize demand-side flexibility, as 63% of EV charging is yet uncontrolled in France. A major challenge appears to be that some barriers for EV development (especially the reduction of charging times, even for local mobility) may be in contradiction with smart charging diffusion.

Sensitivity studies	Increased EV flexibility		Impacts on EV demand flexibility	
	Low gas prices	High gas prices		
Gas prices / Electricity generation mix	Low gas prices	High gas prices	Very high	
Smart charging diffusion	No smart-charging  63 %	37 %  100% EVs smartly charged	High	
Smart charging modes	Time-of-use tariff  75 %	Smart unidirectionnal  25 %	V2G  < 1%	Incremental
Daily or weekly flexibility	Daily flexibility (each EV fully charged at every charging session) 	Weekly flexibility	High / Moderate (depending on smart-charging mode)	
Connection behavior	When needed  75 % (BEVs)	As much as possible  25 % (BEVs)	Medium	
V2G injection limitation	Limited injection (one additional battery cycle per week) 	Unlimited injection	Medium	
Time-of-use profiles	"Basic" tariff 	Optimized (daily)	Optimized (weekly)	Medium
Other battery flexibility for the grid	Several GW of stationary batteries	No other battery flexibility	Low	

 EV Flexibility in France in 2021

Figure 5.1: Main parameters that have an impact on EV flexibility and its current development status in France².

5.2 Further work

The work conducted in this thesis raises a large number of additional research topics, either directly related or ancillary to our joint transport-electricity system analysis methodology, and in a variety of research areas (economics, electricity network science, business models, consumer incentivization, and environmental analysis).

Studying the other aspects of electricity system flexibility

In the introduction, we identified 5 main areas of EV-electrical system interaction (generation and network investment, hourly optimal dispatch, grid congestion,

²See *Enedis (2020)* in the Bibliography of Chapter 4 for more information about the current development of EV flexibility in France

short term markets and grid frequency) and this thesis focused on a single aspect, optimal economic dispatch of electricity generation, which seemed relevant in the medium term and a research gap in the academic literature for the French system.

A question directly underlying this work is the comparison of the interest of EV smart charging relative to these 5 aspects. Such work has already been carried out on historical data, but it also seems relevant to study these interactions on a prospective horizon, and by integrating EVs in power system models to go beyond the price-taker hypothesis. In addition to comparing the benefits of EVs in each case, it is also interesting to study if the EV demand-side flexibility required for these aspects are contradictory or cumulative. For instance, we encourage studying, under European zonal markets, whether synchronizing EV consumption with solar/wind generation at the national level to minimize generation costs will induce network congestion, given that the consumption and production sites are not always at the same location.

Please note that such an analysis seems very complicated to carry out. Indeed, it is important to use a scenario/data set that it will be possible to study on all the aspects mentioned above, including prospective network data, at the national and continental scale, and data for several markets, as well as the related modeling tools.

Finally, even if this kind of study were to be completed, one should keep in mind that these comparisons remain very specific to a spatio-temporal framework. For example, it is expected that for very congested grids, as in some regions of the US, the value of EV flexibility for grid flows will be higher than in France, where the distribution and transport grids are already sized for high electric demand.

Additionally to studying other flexibility objectives, one could also study the competition between EV demand and other demand-side flexibility sources, mainly electrolyzers, industrial and other flexible residential appliances, in order to identify which flexibility sources are the most adapted to each aspect mentioned here (hourly dispatch, grid congestion, frequency regulation, etc.).

Incentives to EV smart charging

The work of this thesis was conducted from the central point of view of the electricity system. This choice is relevant to study long-term "optimal" EV flexibility, but requires additional studies on how to incentivize EV users to accept smart charging in order to achieve the cost and emission reduction of electricity generation modeled throughout this dissertation.

On the one hand, a relevant topic of tariff design emerges, for instance through 'willingness to accept' studies (to be compared with the result of analyses such as those conducted in this thesis, battery degradation costs and to the cost of additional infrastructure required for smart charging, such as bidirectional chargers and communication systems). On the other hand, incentivizing demand-side flexibility could go beyond economic issues, either by notifying EV owners how much carbon emissions the smart charging of their EVs has saved, or by constraining

EVs to be charged off peak at specific locations, such as at work, where vehicles usually stay parked much longer than average charging time.

An underlying question is also the allocation of EV flexibility income between the different actors involved in EV flexibility: the EV owner, electric system operators, the state (through potential taxes), the charging point operator, the car manufacturer and the aggregator (for dynamic smart charging). This distribution has been studied from a game theory point of view for the case of frequency regulation with V2G. However, for EV optimal charging times that minimizes electricity generation cost, the equation is slightly more complex, with smart charging modes that involve different actors (e.g., time-of-use charging does not require aggregators or data from the car manufacturer), and charging points that belong to either a private operator, a public operator or the EV owner (with different technical requirements).

Integration EV modeling into environmental studies

In this thesis, beyond the purely economic aspect, we have also proposed a methodology to estimate the benefits of EV charging flexibility for the reduction of electric generation carbon emissions. Thus, in environmental studies, based on life-cycle analysis, comparing the relevance of thermal, battery electric, hydrogen and hybrid vehicles (usually based on averaged electricity generation emissions data, without taking into account any smart charging), it could turn out interesting to add to the comparison smartly charged EVs, based on results described in this thesis.

In addition, other issues such as the use of second-life EV batteries for the electric system require a similar analysis methodology to estimate their environmental gain.

Mobility in a changing world

Finally, to open up the spectrum of analysis, the methodology proposed in this thesis also invites to be declined for a large number of prospective scenarios, related to the evolution of the transport and electricity generation sectors in our changing world, in the spirit of fast reduction of fossil fuel consumption.

Among others, we can mention the effect of a reduction in the mass of individual vehicles, the evolution of urban planning and behaviors inducing a modal shift towards public transport and soft mobility (which could reduce the distances traveled in individual vehicles as well as the travel speeds), a rise of carpooling, a strong growth of public EV fast chargers rather than slow chargers at home, the development of innovative mobility solutions such as autonomous vehicles and mobility as a service, the electrification of other means of transport (especially trucks and buses), a stronger decentralization of electricity production, or other innovations to be discovered and societal changes that are yet to happen.

A - The impact of EV smart charging on the grid

In this appendix, we propose an analysis of the impact on the transmission grid of some EV load curves computed during this manuscript (in Chapter 3 and 4). In the literature review of this thesis, this topic has been identified as a gap in the academic literature.

For this purpose, the imaGrid software, developed by RTE, is used, as well as data from a 2035 scenario, based on France's *Programmation Pluriannuelle de l'Energie* (PPE), for the development of the transmission network and generation sources in France. A study area composed of 5 departments in the North of France (departments n° 59, 60, 62, 76 and 80) was selected, where an easily accessible study was available. This area has three main characteristics: high renewable generation (especially wind) in rural areas, and nuclear reactors in the North of the area, along with a strong electricity transmission grid around these nuclear plants, while the major cities are located North and East of the zone.

Our methodology is based on the Load Flow analysis of this study area (at hourly intervals), which allows us to calculate the flows on the 404 lines (of the transmission grid only, above 63 kV) and the load of the 80 transformers in the area, for several generation and consumption scenarios in the area. For example, Figure A.1 shows the power flow on a selected line, compared to the capacity of the line (which depends on the temperature and therefore on the season). We observe that this line is congested on several time steps, one of which is identified.

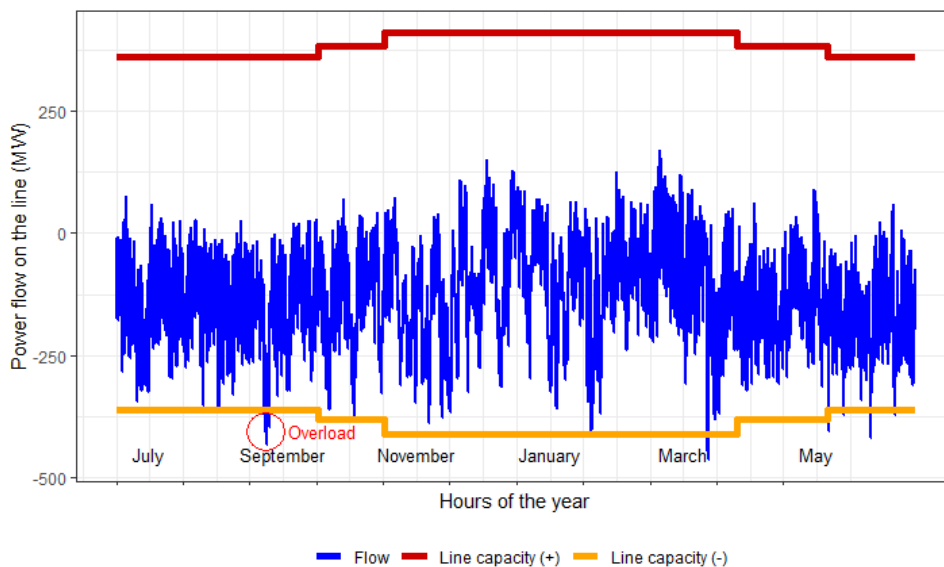


Figure A.1: Annual evolution of the power flow on a selected line (between nodes ANSER and ZBERG)

Thus, we can extract indicators on the network load, such as the number of

time steps where the network is congested, or the average overload power (compared to the line capacity).

For our comparison here, the previously calculated load curves are reused. Since our simulations are for 2040 and with different electricity mix and weather data, we cannot adapt the load curves of dynamic smart charging modes (smart unidirectional and V2G). By 2035, on the scenario trajectory, 50% of EVs are electrified in France, so the consumption data are weighted accordingly.

Thus, we will compare 6 scenarios: adding uncontrolled and time-of-use load curves to the base case, for 3 different EV diffusion scenarios: homogeneous diffusion in the population, urban diffusion (EVs homogeneously distributed among urban areas dwellers) and rural diffusion (every vehicle is an EV in rural areas, where are located 26% of the vehicles in the area, and the remaining EVs are homogeneously affected within urban areas).

The results obtained, presented in Figures A.2 and A.3 show that EV diffusion is a parameter with a strong impact on network congestion, with a more constrained network when EVs are added in urban areas. On the other hand, the time-of-use control presented seems to slightly increase network constraints.

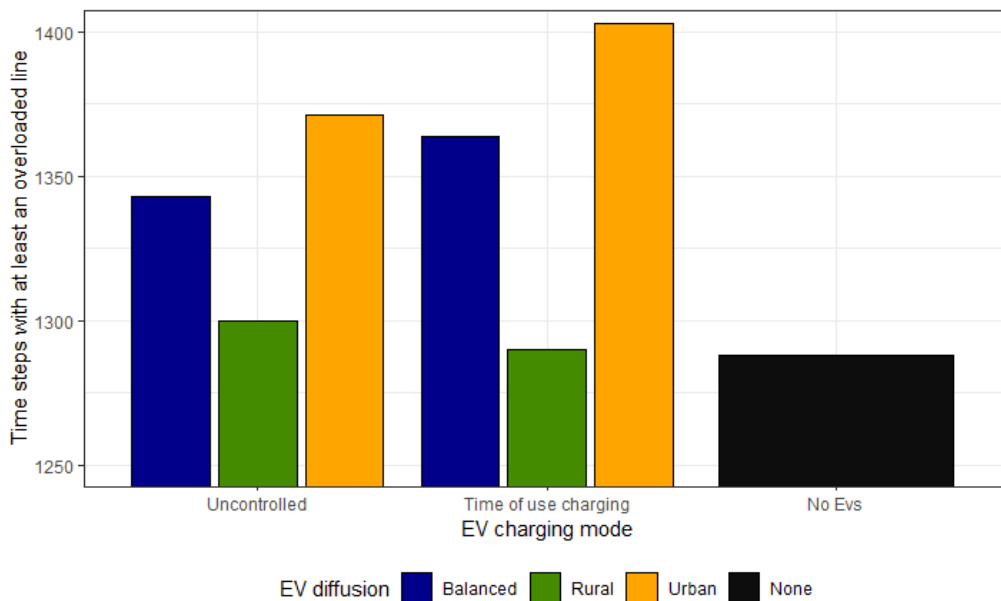


Figure A.2: Time step of the year with at least one overloaded line in the zone of study (Load Flow simulation)

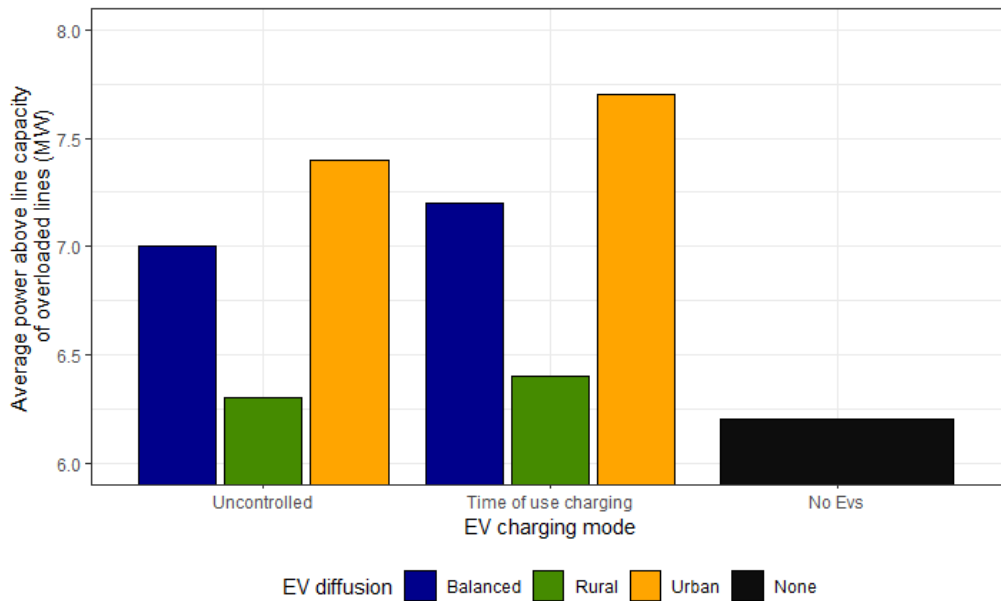


Figure A.3: Average overload power of overloaded lines in the zone of study (Load Flow simulation)

These first results need to be confirmed with studies on other areas, and using data calculated for the same time horizon and the same electricity mix data.

To go further in this analysis, simulating the network in Optimal Power Flow (OPF) will allow to estimate the cost to compensate the congestion on the network, which allows to compare the economic interest of smart charging EVs for network purposes and the reduction of electric generation costs computed in Chapter 4.

B - Résumé en français

Cette thèse vise à étudier l'interaction entre les véhicules électriques (VE) et les systèmes électriques. Pour ce faire, un plan en quatre chapitres est utilisé, dont les principaux messages sont présentés dans la suite de ce résumé en langue française.

Chapitre 1 : Introduction générale

Ce chapitre est composé de cinq parties qui permettent d'introduire et cadrer le sujet de cette thèse.

Tout d'abord, le chapitre commence par un rappel des travaux du GIEC, ainsi qu'une mise en contexte des deux secteurs étudiés dans cette thèse, le transport et la production d'électricité, au sein des émissions de carbone françaises et européennes.

Ensuite, l'historique de l'évolution des pratiques de mobilité en France est présenté, ainsi que les perspectives de réduction des émissions du secteur. La mobilité électrique apparaît comme une des principales solutions pour agir sur le levier de l'intensité carbone de l'énergie de propulsion des véhicules. Les perspectives d'électrification des différents modes de transport sont abordées, et ce sont les véhicules individuels qui ont le potentiel le plus élevé (en consommation totale) ainsi que les bus et camions dans une moindre mesure.

Egalement dans une perspective de décarbonation, la production électrique dans le Monde (ainsi qu'en UE et en France) est en tendance d'évolution vers des mix comportant plus d'énergies renouvelables (en particulier solaire PV et éolien), en remplacement de centrales fossiles carbonées. Historiquement, ces dernières étaient responsables d'une grande part de la flexibilité des systèmes électriques pour assurer l'équilibre offre-demande, ce qui implique de développer d'autres solutions de flexibilité, notamment la flexibilité de la consommation.

Ainsi, les véhicules électriques (VEs) constituent une part du potentiel de flexibilité de consommation à horizon prospectif. Plusieurs domaines d'interaction entre les VEs et le système électriques sont identifiés, pour répondre aux problèmes de flexibilité du système électrique à différentes échéances temporelles et sur divers aspects (optimisation de l'utilisation de moyens de production, fréquence du réseau, flux sur le réseau). Ainsi, divers modes de pilotage de la recharge de ces VEs se développent, qui sont étudiés dans la suite des travaux.

Enfin, le cadrage du sujet de cette thèse sur les véhicules individuels électriques, ainsi que le sujet du dispatch électrique européen à horizon prospectif 2040 est proposé, afin de répondre aux deux questions de recherche :

Comment modéliser l'intégration prospective aux systèmes électriques une diffusion massive de véhicules électriques ?

Comment comparer les principaux modes de pilotage de la consommation des VEs, et quels paramètres impactent le plus le potentiel de flexibilité de consommation ?

Chapitre 2 : Revue de littérature des modèles de charge naturelle et de pilotage des véhicules électriques

Dans ce chapitre, nous effectuons une revue de la littérature académique des modèles permettant de générer des données de connexion et de consommation des VEs, ainsi que des modèles relatifs à leur pilotage.

Différentes catégories de modèles sont identifiées, avec en général un sujet de recherche adapté qui leur est associé. Nous présentons aussi les optimisations présentes dans la littérature relatives au pilotage des VEs : minimiser le coût de recharge, limiter l'appel de puissance local ou les congestions sur le réseau, maximiser la part d'énergie renouvelable autoconsommée ...

La plupart des articles comparés se focalisent soit sur le transport, soit sur le système électrique, avec une modélisation approximative de l'autre aspect. En particulier, beaucoup d'articles utilisent des données de marché électrique historiques, et considèrent les VEs comme des price-takers. Cette approche est pertinente à court terme, tant que les VEs constituent une part négligeable de la consommation électrique totale. Cependant, pour des études prospectives à moyen et long terme, il semble important de modéliser séquentiellement les secteurs du transport et de la production électrique afin de dépasser cette approximation.

Finalement, nous concluons ce chapitre en identifiant l'approche de modélisation la plus pertinente au vu de la littérature pour chacun des principaux sujets de recherche relatifs à l'intégration des VEs dans les systèmes électriques.

Chapitre 3 : Modèle prospectif de demande des véhicules électriques

A la suite de la revue de littérature effectuée dans le chapitre 2, l'approche la plus adaptée au sujet de recherche de cette thèse a été identifiée puis développée. Ainsi, le modèle utilisé pour générer les données de connexion et de consommation des VEs est décrit dans ce chapitre.

Les données d'entrée sont composées de deux éléments. Dans un premier temps, la liste des hypothèses devant être sélectionnées est indiquée. Ensuite, les données individuelles de déplacement proviennent le plus souvent dans la littérature d'enquête transport, menées à la maille locale ou nationale. Pour ces travaux, nous avons traité les enquêtes mobilités 2008 et 2019 en France (qui ne diffèrent que peu sur l'utilisation des véhicules individuels). Les déplacements sont notamment séparés selon plusieurs paramètres qui influent sur les données de mobilité (distances et horaires des déplacements), tels que la zone de résidence du possesseur (rural, urbain ou métropole) et la catégorie socio-professionnelle (VE utilisé pour se rendre au travail ou pour autres motifs). Une séparation est également réalisée entre les trajets de mobilité locale et les trajets longue distance, qui nécessitent parfois une recharge haute puissance en cours de trajet.

Les étapes de modélisation sont ensuite présentées : génération des paramètres des véhicules, génération des plannings de déplacement, calcul des consommations liées aux déplacements et de l'emplacement des VEs, calcul de la demande

électrique des VEs, puis agrégation des résultats par catégories (type de véhicule, lieu de recharge, zone ...).

Notre modèle est basé sur des simulations Monte-Carlo, qui consistent en la génération d'un très grand nombre de tirages aléatoires sur les données d'entrée, afin d'obtenir des profils moyens statistiquement représentatifs.

Le modèle proposé possède l'avantage de pouvoir prendre en compte une large diversité de scénarios de diffusion des VEs, de leur infrastructure de recharge, ainsi que des comportements des usagers (se connecter systématiquement, quand l'état de charge de la batterie est faible ou en week-end). De plus, même si la thèse se focalise sur les véhicules individuels électriques et hybrides rechargeables, une adaptation du modèle pour traiter les autres vecteurs énergétiques (hydrogène et biocarburants) ainsi que les bus et camions est présentée.

Pour finaliser ce chapitre, le modèle est appliqué sur un cas d'étude de diffusion massive de véhicules électriques en France à horizon 2040, avec environ deux tiers de la flotte électrifiée. Les courbes de charge et de disponibilité aux bornes liées à plusieurs variantes sont illustrées.

Chapitre 4 : Flexibilité de la consommation des véhicules électriques pour le dispatch du système électrique

A partir des données de connexion et des besoins énergétiques des VEs générés grâce au modèle présenté dans le chapitre 3, ce chapitre vise à intégrer les VEs à des simulations du dispatch du système électrique européen (en prenant en compte les moyens de production dans chaque pays ainsi que les capacités d'échange entre zones de prix électriques).

Les millions de VEs potentiellement pilotés sont regroupés au sein d'un objet électrique équivalent au sein de notre modèle. Les contraintes utilisées pour modéliser cette agrégation et le pilotage de la recharge de ces VEs sont décrites et justifiées dans ce chapitre. Ces dernières permettent d'étudier un grand nombre de modes de pilotage qui émergent : pilotage à partir de signaux tarifaires (basiques ou améliorés), pilotage dynamique unidirectionnel (*smart charging*) ou pilotage dynamique bidirectionnel (vehicle-to-grid, *V2G*).

Nous comparons ensuite ces modes de pilotage selon le gain économique et d'émissions de carbone qu'ils apportent au dispatch des moyens de production électriques, basé sur un cas d'étude à horizon 2040 dans un système électrique à forte pénétration des moyens de production renouvelables. Dans notre scénario de référence, le pilotage dynamique unidirectionnel de la charge des 24 Millions de VEs réduit le coût de production d'électricité d'environ 1 G€ annuels, ainsi que les émissions associées de 2.4 MtCO₂-eq.

Les paramètres qui influent le plus sur la valeur de la flexibilité de la charge des VEs sont le prix des combustibles (en particulier le gaz), la diffusion des modes de pilotage (dans l'ordre croissant de valeur : signaux tarifaires, *smart charging* et *V2G*), ainsi que la possibilité de procurer de la flexibilité hebdomadaire en permettant le report de la charge d'un ou quelques jours. A horizon 2040 à fort

développement du solaire PV, il apparaît que le milieu de journée est un des moments de la journée où les coûts de production électrique sont les plus bas, donc la connexion d'une part des VE en milieu de journée est également souhaitable pour réduire les coûts et émissions du système électrique.

Conclusion générale

Pour conclure ce manuscrit, les principaux messages de la thèse sont regroupés.

Il apparaît que le pilotage de la recharge est peu développé en France en 2021, de l'ordre de 37% des usagers. Ainsi, les travaux menés dans cette thèse appellent à développer davantage la flexibilité de consommation des VE dans les années à venir, par les différents modes de pilotage identifiés, selon l'acceptabilité par les usagers, au vu des gains estimés à horizon 2040.

Enfin, des sujets de recherche émergents connexes à ce travail de thèse sont évoqués, notamment sur (1) l'étude de la flexibilité de la recharge des VE pour d'autres aspects du système électrique que le dispatch optimal, (2) les incitations des usagers au pilotage de la recharge, (3) l'étude environnementale de l'intérêt du pilotage des VE et (4) le besoin de déclinaison du cadre d'analyse construit dans cette thèse pour d'autres scénarios de la mobilité dans notre monde en évolution vers la neutralité carbone.

Titre: Impacts et opportunités des nouvelles mobilités pour le système électrique

Mots clés: Véhicules électriques, Système électrique, Flexibilité de consommation, Transition énergétique

Résumé: Dans le cadre de la réduction de l'impact environnemental du secteur des transports de personnes et de marchandises, la mobilité électrique est amenée à se développer dans les années à venir. La recharge des véhicules électriques (VE) présente un potentiel intrinsèque de flexibilité de la consommation électrique, du fait de périodes de connexion généralement plus longues que nécessaire pour recharger le véhicule, en particulier pour les véhicules individuels. Cette thèse se focalise sur l'étude de cette flexibilité de consommation, qui permet de réduire les coûts opérationnels et les émissions de carbone du système électrique, en particulier à horizon prospectif de forte diffusion de la mobilité électrique. Afin de traiter ce sujet de recherche, l'introduction présente les enjeux de décarbonation des secteurs du transport et de production d'électricité en France ainsi que leurs

interactions. Dans un second temps, les principales méthodes de modélisation des VE et de leur impact sur différents aspects du système électrique sont décrites. Ensuite, un modèle pour obtenir des données de connexion et de demande électrique de ces véhicules, à partir de données d'enquête transport, est proposé. Finalement, l'intégration de ces données dans un modèle de dispatch horaire du système électrique Européen est présentée, puis illustrée sur diverses hypothèses relatives au développement de la mobilité électrique à horizon 2040. Cette méthodologie permet ainsi la comparaison des principaux modes de pilotage de la recharge des VE, ainsi que l'identification des paramètres qui influent le plus sur la valeur de cette flexibilité de consommation : le prix des combustibles fossiles ainsi que les variantes sur la diffusion des modes de pilotage des VE.

Title: Impacts and opportunities of new mobilities for the electrical system

Keywords: Electric vehicles, Electrical system, Demand-side flexibility, Energy transition

Abstract: In the context of environmental impact reduction of the passenger and freight transport sectors, electric mobility is set to grow in the coming years. Electric vehicle (EV) charging has a natural potential for electricity demand flexibility as connection periods are generally longer than the necessary charging time, especially for individual vehicles. This thesis focuses on the study of this demand-side flexibility, which induces a reduction of the operational costs and carbon emissions of the electricity system, in particular in scenarios with substantial diffusion of electric mobility. The analysis begins with a discussion of the decarbonization pathways of the French transport and electricity generation sectors as well as their mutual interactions. This is followed by a descrip-

tion of the state-of-the-art methods for modeling EVs and their impact on different aspects of the electricity system. A model to generate EV connection and electrical demand data based on transport survey data is then proposed. Finally, the integration of these data in an hourly dispatch model of the European power system is presented and illustrated on various scenarios of the electric mobility development by 2040. This methodology allows the comparison of the foremost EV smart charging modes, as well as the identification of the parameters that most influence the value of this demand-side flexibility: the price of fossil fuels and the level of diffusion of the various EV smart charging modes.