Optimizing the electricity demand of electric vehicles
Creating value through flexibility

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Optimizing the electricity demand of electric vehicles: creating value through flexibility

A thesis submitted to attain the degree of

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(Dr. sc. ETH Zurich)

presented by

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Preface

This thesis was written during my time as a researcher at the Power Systems Laboratory of the ETH Zurich between 2010 and 2015.

I would like to thank my thesis supervisor Prof. Dr. Göran Andersson for his guidance. I really appreciated the trust and freedom given to conduct this work.

Thanks also to Prof. Dr. Ian Hiskens, the co-examiner of this thesis, for his feedback and fruitful discussions.

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During my time at the Power Systems Laboratory I had the chance to supervise many Semester and Master thesis. I’d like to thank the students whose projects I supervised for their hard work and excellent results, that have certainly contributed to this thesis.

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Abstract

This thesis focuses on models of plug-in electric vehicle (PEV) demand flexibility, as well as on methods to generate value from this flexibility, by reducing the costs of procuring the charging demand, and by providing ancillary services.

First, individual and aggregated models of PEV charging flexibility, based on driving patterns from a transport simulation, are introduced. Specifically, flexibility is represented as a set of linear power and energy constraints, which can be used in different optimization problems. For the aggregated representation (virtual battery), a scenario-based robust approach to address driving pattern uncertainty is introduced.

Second, different approaches to minimize the costs of procuring the charging demand are presented, categorized along three dimensions: centralized/decentralized control, unidirectional/bidirectional communication, strategic/cooperative decision-making. Mainly, the following methods are introduced: A) A bidding strategy for a PEV aggregator, based on complementarity modeling, B) a bidding strategy for individual PEVs in a market-based control context, based on reinforcement learning, C) a cooperative decentralized scheduling approach, based on the Alternating Direction Method of Multipliers, D) a method to determine optimal time of use tariffs in a framework where PEVs respond optimally to exogenous price signals, and E) a hierarchical control approach combining the aggregator’s bidding strategy and the cooperative decentralized scheduling.

Third, the aggregator’s bidding strategy and the cooperative decentralized scheduling are extended to use the PEVs’ flexibility to provide ancillary services (frequency regulation and real-time balancing), in addition to minimizing charging costs. Both unidirectional and bidirectional charging options are considered in this context, as well as different
settings of the service contract.

Finally, a case study on the impact of increasing PEV penetrations on the Swiss power system is presented, for different possible future demand, supply and PEV penetration scenarios.

The concepts and results presented in this thesis show that PEVs, as flexible loads and distributed storage devices, can be a valuable resource for power systems.
Kurzfassung


Drittens werden die Bieterstrategie des Aggregators und der kooperative dezentrale Ansatz erweitert, um die Flexibilität der PHEF nicht
nur zur Minimierung von Energiebeschaffungskosten zu nutzen, son-
dern auch zur Bereitstellung von Systemdienstleistungen (Frequenzre-
gelung und Echtzeit-Balanceausregelung). Sowohl unidirektionale und
bidirektionale Lademöglichkeiten, als auch unterschiedliche Ausgestal-
tungen des Dienstleistungsvertrages werden in diesem Zusammenhang
berücksichtigt.

Schliesslich wird eine Fallstudie zu den Auswirkungen von Elektromo-
bilität auf das Schweizer Energiesystem für verschiedene zukünftige
Nachfrage-, Angebots- und PHEF Durchdringungsszenarien vorgestellt.
Die Konzepte und Ergebnisse dieser Arbeit zeigen, dass PHEF als fle-
xible Lasten und verteilte Speicher eine wertvolle Ressource für das
Energiesystem darstellen können.
List of Acronyms

**ADMM** Alternating Direction Method of Multipliers
**AGC** Automatic Generation Control
**BGM** Balance Group Manager
**CDF** Cumulative Distribution Function
**CHP** Combined Heat and Power
**DSO** Distribution System Operator
**EU** European Union
**KKT** Karush Kuhn Tucker
**LMP** Locational Marginal Price
**MILP** Mixed Integer Linear Programming
**MPEC** Mathematical Problem with Equilibrium Constraints
**OPF** Optimal Power Flow
**PEV** Plug-in Electric Vehicle
**RES** Renewable Energy Source
**SOC** State of Charge
**TOU** Time of Use
**TSO** Transmission System Operator
**V2G** Vehicle to Grid
List of Symbols

Indices

\( v \)  vehicle
\( t \)  time step (of duration \( \Delta t \))
\( n \)  network node
\( d \)  demand bid
\( s \)  supply bid
\( m \)  iteration
\( r \)  market scenario
\( k \)  driving pattern and reserve request scenario
Individual PEV

Variables related to each vehicle $v$, potentially time-dependent, i.e. indexed with $t$. These variables have the superscript $V$.

- $C^V_v$: Battery capacity
- $E^V_{vt}$: Battery energy content
- $E^V_{vt,\text{cons}}$: Energy consumption
- $E^V_{vt,\text{fuel}}$: Energy consumption covered by fuel
- $E^V_{vt,\text{low}}$: Lower trajectory for the energy in the battery
- $E^V_{vt,\text{low,free}}$: “Free” lower trajectory for the energy in the battery
- $E^V_{vt,\text{up}}$: Upper trajectory for the energy in the battery
- $P^V_{vt}$: Charging power
- $P^V_{vt,\text{max}}$: Maximum charging power
- $P^V_{vt,\text{min}}$: Minimum charging power
- $P^V_{vt,\text{low}}$: Lower trajectory for the charging power
- $P^V_{vt,\text{low,}\text{V2G}}$: Lower trajectory for the charging power with V2G
- $P^V_{vt,\text{up}}$: Upper trajectory for the charging power
- $P^V_{vt,\text{up,}\text{V2G}}$: Upper trajectory for the charging power with V2G
- $\text{SOC}^V_{v,\text{max}}$: Maximum state of charge
- $\text{SOC}^V_{v,\text{min}}$: Minimum state of charge
- $\eta^V_v$: Charging efficiency

Aggregated model (virtual battery)

Variables related to the virtual battery at each node $n$, potentially time-dependent, i.e. indexed with $t$. These variables have the superscript $A$.

- $E^A_{nt}$: Aggregated energy content
- $E^A_{nt,\text{arr}}$: Aggregated energy contribution of arriving PEVs
- $E^A_{nt,\text{dep}}$: Aggregated energy contribution of departing PEVs
- $E^A_{nt,\text{max}}$: Maximum aggregated energy content
- $E^A_{nt,\text{min}}$: Minimum aggregated energy content
- $E^A_{nt,\text{min,free}}$: Minimum aggregated energy content under more relaxed conditions
- $P^A_{nt}$: Aggregated charging power
- $P^A_{nt,\text{max}}$: Maximum aggregated charging power
- $P^A_{nt,\text{min}}$: Minimum aggregated charging power
- $\eta^A_{nt}$: Aggregated charging efficiency
List of Symbols

Day-ahead market

Variables used in the market clearing model, e.g. related to supply (superscript S), demand (superscript D), and aggregator demand bids (superscript A).

- $c_D^{dt}$: Demand bid price
- $c_S^{st}$: Supply bid price
- $c_A^t$: Aggregator demand bid price
- $P_D^{D,max}$: Demand bid volume
- $P_S^{S,max}$: Supply bid volume
- $P_A^{A,max}$: Aggregator demand bid volume
- $\lambda^t$: Market clearing price (dual variable)

Ancillary services

Variables related to ancillary services (regulation, wind balancing).

- $\Delta E$: Virtual battery energy shift
- $C_t^+$: Up-reserve capacity offered by aggregator
- $C_t^-$: Down-reserve capacity offered by aggregator
- $e_t^+$: Up-reserve request
- $e_t^-$: Down-reserve request
- $f_t$: Wind forecast
- $g_t^+$: Up-reserve capacity payment
- $g_t^-$: Down-reserve capacity payment

Joint chance constraint

Variables related to the joint chance constraint including the virtual battery’s power and energy constraints.

- $\epsilon$: Violation parameter
- $\beta$: Confidence parameter
- $\delta$: Random variables at individual vehicle level
- $\omega$: Random variables at virtual battery level
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Chapter 1

Introduction
1.1 Background and motivation

The electrification of transportation has received increasing attention in the last decade, mainly for two reasons. First, it is seen as a possibility to reduce dependence on oil, a scarce energy resource associated with geopolitical concerns. Second, in the context of climate change, an increasing number of policies are being introduced that aim at a decarbonization of the economy, i.e. at reducing emissions of CO$_2$ and other greenhouse gases. In 2012, transportation was responsible for 63.7% of the total final oil consumption worldwide [1], and for 23% of the global CO$_2$ emissions from fuel combustion [2].

An important component of the transportation sector is passenger cars. In the following, the term plug-in electric vehicles (PEVs) is used to refer to both pure electric vehicles (also called battery electric vehicles), and plug-in hybrid electric vehicles, which have a combustion engine in addition to the electric motor. With an electricity-production mix of low CO$_2$ intensity, PEVs could significantly lower life-cycle greenhouse gas emissions compared with conventional combustion engine vehicles [3, 4]. In the European Union (EU), mandatory targets have been set for the average CO$_2$ emissions of new passenger cars (130g/km by 2015 and 95g/km by 2021) [5], which create incentives for automobile manufacturers to introduce PEV models. PEVs still represent a very small percentage of the passenger car stock worldwide at less than 0.1%. However, PEV sales have been increasing in the last several years [6]. In Norway, where policies encourage consumers to purchase PEVs, PEVs made up almost 16% of the total number of vehicles newly registered in 2014 [7].

Decarbonization policies have also created a shift in electricity generation from fossil fuel power plants towards Renewable Energy Sources (RES). Although hydro power has been exploited in the past, other forms of RES, such as solar, wind, and geothermal power, are becoming increasingly important. In the EU, the Renewable Energy Directive sets a binding target for RES to represent 20% of the final energy consumption by 2020 for the EU as a whole [8]. In this context, EU countries have adopted National Renewable Energy Action Plans, which include sectorial targets for the electricity sector, among others. In Switzerland, the Energy Strategy 2050 aims at a progressive phase-out of nuclear energy, with RES as one of the means to fill the resulting gap [9]. In this country, electricity production from RES other than hydro power has
1.1. Background and motivation

increased by 40% between 2011 and 2013 [10, 11]. Key characteristics of some of the new RES are intermittence, distributedness and limited controllability. These characteristics apply to solar photovoltaic and wind power, the dominant new RES.

Since RES units are often small, distributed components connected to the distribution system – photovoltaic units being the most common example – the traditional approaches to the planning and operation of distribution grids are being challenged. For example, some distribution grids already experience reverse power flows. Apart from their influence on local distribution grids, intermittent RES, such as photovoltaic and wind power, also have a system-wide impact due to the uncertainty of their weather-dependent output, and the fact that they can only be partially controlled, through curtailment. Therefore, there is an increasing need for flexibility in power systems [12, 13].

This additional flexibility could come from the demand-side of electricity (e.g. from thermal loads such as water boilers and air conditioning units, or PEVs, which are the focus of this thesis). This concept is generally known as Demand Response. In order to fully unlock the flexibility of demand beyond the currently existing, relatively simple schemes, such as Time of Use (TOU) tariffs and ripple control, communication technologies play an increasingly important role. Therefore, another related trend is the growing use of information and communication technologies in the electricity distribution grid, which were previously mostly present in the high-voltage transmission grid. Grids with increased communication and control capabilities are often called smart grids [14]. Smart grids use monitoring, control, and communication technologies to create a more sustainable and reliable electrical grid by better integrating distributed resources such as photovoltaic panels, wind turbines, batteries and flexible loads. A related concept is the Virtual Power Plant [15], an aggregation of such distributed resources that is monitored and controlled by a central entity for economic or technical purposes.

From the perspective of the electrical grid, the rising number of PEVs may present a challenge, leading to electricity network congestion, accelerated transformer aging and/or undervoltage problems [16–19]. However, PEVs represent a particularly flexible load, well suited for demand response. Vehicles are typically parked most of the time (more than 90% of the time on average [20], and the time required to recharge their batteries is generally much shorter than the time they remain parked. Therefore, charging could be shifted in time without having a negative
impact on the user. Moreover, the energy stored in the vehicles’ batteries could be discharged back to the grid (a concept called Vehicle to Grid, or V2G). V2G increases the value of PEVs as distributed resources, but it creates additional cycling of the batteries, and therefore faster degradation.

Creating value through flexibility – aggregator roles and interactions

PEV charging (and discharging) flexibility can be used for multiple purposes [21–23], namely to reduce the costs of procuring the electricity for charging, or to provide (ancillary) services for network operators or other parties. Typically, an intermediary agent between the PEVs and other entities of the electricity sector (e.g., energy suppliers, power market operators and network operators) is envisaged, that is generally known as aggregator. The integration of the aggregator agent into the electric power system, and the related roles, services and business models of this new actor are discussed in detail in [21, 22, 24–26]. The aggregator clusters a large number of PEVs (and more generally other flexible loads/storage devices), which individually have only a small impact on the system, but as a group can be used as a significant resource. The aggregator is envisaged to directly or indirectly manage vehicle charging [22], to generate value from the flexibility of the PEV fleet, and share this value with PEV owners.

Figure 1.1 shows the potential interactions between the aggregator and other actors in the electricity sector. This sector has undergone important changes in the recent decades through the liberalization of electricity markets and the unbundling of integrated utilities. Before detailing the different ways to create value from the PEV aggregation’s flexibility, the different parties depicted in Fig. 1.1 are described, see also [22, 26]. Distribution System Operators (DSOs) are in charge of planning, operating and maintaining the distribution network (medium and low voltage). Transmission System Operators (TSOs) perform similar tasks at the transmission network level (high voltage). They are in charge of ensuring that the balance between demand and supply of electricity is maintained, in order to keep the system frequency within an acceptable band. Balance Group Managers (BGM) are responsible for balance groups (also called balancing groups), an accounting construct that clusters loads and generators. Balance groups are penalized
for real-time deviations from their scheduled energy profile. Power market operators are in charge of running power exchanges (both spot and derivative markets). Spot power markets typically comprise day-ahead and intra-day markets. Energy suppliers (also often referred to as load serving entities, energy retailers or energy service providers) are entities which supply their portfolio of loads by contracting energy on the power market or through brokered or direct mutual agreements with power producers. Other entities acting on the power market (not depicted in Fig. 1.1) are power producers (also called generating companies), and traders. Traders buy and sell electricity on the wholesale market to generate profit through arbitrage. The electricity sector model described here fits the model of most European countries better than the USA model. In the USA, an Independent System Operator (ISO) typically performs the tasks of both the TSO and the power market operator described here. The concept of balance groups also does not exist in the USA system.

![Diagram]

**Figure 1.1**: PEV aggregator's interactions creating value through charging/discharging flexibility. DSO: Distribution System Operator, TSO: Transmission System Operator, BGM: Balance Group Manager.

In the following, the different ways to create value through charging (and discharging) flexibility depicted in Fig. 1.1 are discussed. At low PEV penetrations, energy suppliers could provide incentives to customers owning PEVs to shift their charging to hours with low prices. This
could be achieved through appropriate TOU tariffs \cite{16,18}. Thereby, the energy supplier would reduce the costs of procuring electricity, in power markets or through other types of contracts, and would be able to increase its profits and at the same time offer attractive tariffs to PEV owners. At higher PEV penetrations, a PEV aggregator could act as an energy supplier for PEVs, and purchase energy on behalf of the vehicles, e.g. in the spot market \cite{27–32}. PEV aggregations could also provide different types of ancillary services \cite{20,22}. These could be local ancillary services (for DSOs), such as voltage control \cite{33,34}, and peak-shaving \cite{35}, or system-wide ancillary services (for TSOs), such as primary \cite{36}, secondary \cite{27,28,37–39} or tertiary frequency control \cite{40}. Whereas for TSO services well-established platforms to procure ancillary services exist, there are typically no standard “DSO services”. However, with the increasing penetration of RES in distribution systems, and with the new technical possibilities and business models that arise through the smart-grid paradigm, this type of services are currently under discussion. Another consequence of the growing importance of intermittent RES in the system is an increasing need for real-time balancing. PEV aggregations could provide such balancing services directly to RES power plant managers \cite{41–47} or indirectly via balance groups.

In summary, the PEVs’ flexibility can be used to generate value by 1) reducing the costs of procuring electricity for charging, and 2) providing a range of services for network operators and/or other parties (e.g. balance groups). The term “ancillary services” will be used loosely in this thesis to refer to this range of services. An important difference between the two uses of flexibility is that, whereas reducing the procurement costs comes from the actual shifting of consumption in time, providing services can additionally have a capacity component in the remuneration structure. Specifically, the capacity component implies that a PEV aggregator commits (reserves) upfront a certain capacity to a particular service, and is remunerated for this commitment, independently of whether this reserve is called upon or not in operation.
1.1. Background and motivation

Modeling and optimization aspects

In this context, appropriate methods are needed to a) represent the flexibility of individual PEVs and PEV aggregations, and b) to schedule charging (and discharging) optimally using the available flexibility in order to generate value through the interactions discussed above.

Different sources of uncertainty need to be considered in this context. First, the flexibility of PEVs is very much dependent on driving patterns (arrival and departure times, trip energy consumption) and is therefore subject to forecast errors. Second, the market prices and the bidding behavior of market participants are also not known ex-ante to an aggregator bidding in power markets. Third, the service requests from DSOs, TSOs and BGMs can also be stochastic.

Compared with conventional power plants, which are the common ancillary service providers nowadays, PEVs are not only uncertain resources, as mentioned above, but they are also energy constrained\(^1\). This means that their charging/discharging flexibility at any given point in time depends on previous charging/discharging actions. Therefore, the problem of scheduling charging/discharging optimally is inherently an intertemporal problem. The time scale at which PEVs can store energy is usually considered to be in the range of one day.

Another important aspect is how to approach the task of controlling/incentivizing the demand of PEVs. Three dimensions can be considered in this context. First, charging scheduling decisions can be taken by individual PEVs (decentralized control) or by a central agent (centralized control), typically a PEV aggregator. Second, approaches can rely on bidirectional communication, or be based on the top-down broadcast of prices or control signals. Third, a decision-making agent (aggregator or PEV) can act in a selfish/strategic way, i.e. minimize its charging costs only, or in a cooperative way.

Mainly in the case of centralized approaches, an important challenge lies in developing models for the aggregated flexibility of distributed, uncertain PEV resources that are accurate enough, but are still scalable and have low computational complexity.

Finally, since the PEVs’ flexibility can be used to serve multiple purposes simultaneously, methods to trade off between these different goals

\(^1\)This is also true for storage and pumped hydro power plants, but usually on a longer time scale.
are required: An aggregator would need to co-optimize the costs of procuring electricity for charging and the revenues from providing one or more ancillary services.

1.2 Contributions

The main contributions of this thesis in terms of modeling and optimization are the following:

- A model for the aggregated flexibility of a PEV fleet as a set of probabilistic time-varying power and energy constraints, constructed from samples of driving patterns, and reformulated using a scenario-based robust approach.

- A combined centralized-decentralized hierarchical approach to charging scheduling with the goal to minimize the costs of procuring the charging demand, composed of two levels:
  
  - Upper hierarchy level (centralized): Bidding strategy for the aggregator in the day-ahead market, where the aggregator is modeled as a price-maker and the impact of the aggregator’s bids on prices is taken into account using complementarity modeling. Both uncertainties over market outcomes and driving patterns are taken into account.
  
  - Lower hierarchy level (decentralized): A scalable and flexible method to schedule the charging of individual PEVs in order to follow the aggregated charging profile determined by the upper hierarchy level, based on the Alternating Direction Method of Multipliers (ADMM). Driving pattern uncertainty is considered in the model.

- The centralized and decentralized approaches described above are also extended to co-optimize the costs of procuring electricity for charging and the revenues from providing secondary frequency control (or balancing services). The fleet’s capability to respond to stochastic service requests is modeled in a robust way.

Further, through extensive case studies based on realistic data, this thesis provides some insight into the following aspects:
1.3. Outline of the thesis

- A comparison of charging scheduling approaches, based on three dimensions: 1) centralized vs. decentralized control, 2) unidirectional vs. bidirectional communication, 3) strategic vs. cooperative decision-making.

- An analysis of the impact of different sources of uncertainty on the performance of the different charging scheduling approaches.

- An assessment of the impact of the availability of V2G, and of the characteristics of the frequency control/balancing contracts, on the ability of a PEV aggregator to offer frequency control/balancing services.

1.3 Outline of the thesis

This thesis is structured as follows:

**Chapter 2: Modeling PEVs’ demand flexibility.** In this chapter, individual and aggregated models of PEV charging flexibility are introduced. Specifically, flexibility is represented as a set of power and energy constraints, that are later used in different optimization problems. This chapter also describes how to generate driving patterns, which are an important input to charging flexibility representations.

**Chapter 3: Charging cost optimization.** This chapter focuses on schemes to minimize the costs of procuring the charging demand. Different charging approaches are introduced along the three dimensions mentioned earlier: centralized/decentralized control, unidirectional/bidirectional communication, strategic/cooperative decision-making. Moreover, a hierarchical control approach combining some of these methods is proposed. A case study compares the results of the different approaches, and analyzes the impact of market and driving pattern uncertainty on their performance.

**Chapter 4: Ancillary service provision.** In this chapter, the framework introduced in the previous chapter is extended to not only consider minimizing the costs of procuring the charging energy, but also use the charging (and even discharging) flexibility to provide ancillary services. The chapter focuses specifically on the provision of secondary frequency control and real-time balancing for RES forecast errors. A case study analyzes the available potentials for the mentioned services,
and the tradeoff between the costs of procuring charging demand and the amount of provided reserves. The effects of the availability of V2G, and of the characteristics of the service contracts are considered in this analysis.

Chapter 5: Case study for Switzerland. In this chapter, an analysis of the impact of PEV charging on the Swiss power system is performed. Future electricity supply and demand scenarios, and PEV penetration and composition scenarios are considered for this purpose.

Chapter 6: Conclusion and outlook. Finally, this chapter draws conclusion based on the presented methods and results, and provides some suggestions for future work.

1.4 List of publications

Journal publications


Conference papers


**Book chapters**


**Reports**

The research leading to the results in this thesis received funding from two projects: “Technology-centered Electric Mobility Assessment” (THELMA), and the EU FP7 project “PlanGridEV”. The following reports stem from these projects:


Chapter 2

Modeling PEVs’ demand flexibility
As discussed in the Introduction (§1), vehicles are typically parked most of the time, and the time required to recharge their batteries is generally much shorter than the time they remain parked. Therefore, PEVs can be considered a flexible load, i.e. there are multiple charging profiles that satisfy the mobility needs of the driver. This chapter focuses on models to represent this flexibility, i.e. models that define the set of feasible charging profiles.

Charging flexibility is not only determined by battery and charging infrastructure characteristics, but also by the driving patterns of the vehicles, i.e. by factors such as times of arrival and departure, and trip energy consumption. Therefore, this chapter starts by briefly describing how driving patterns can be obtained from transport statistics and simulation models (§2.1).

The flexibility representations are to be used in optimization problems where the flexibility is used to create value. These optimization problems can be considered from the perspective of individual vehicles (decentralized approaches) or from the perspective of a PEV aggregator (centralized approaches). Therefore, both individual and aggregated representations of charging flexibility are discussed, in §2.2 and §2.3 respectively. Finally, §2.4 concludes the chapter.

2.1 Driving patterns

The electricity demand of PEVs and its associated flexibility are largely dependent on driving patterns. The driving patterns of a vehicle comprise the arrival and departure times, as well as the energy consumption associated with each trip, and the parking locations. Together with the physical characteristics of the battery, such as capacity and charging efficiency, and that of the charging infrastructure, such as maximum charging power, driving patterns determine the set of feasible charging profiles of a given PEV. A feasible charging profile in this context means a charging schedule that covers the mobility needs of the driver, i.e. it does not impact the end-use of the vehicle. The driving patterns used in this thesis stem from the transport simulation tool MATSim [68], described in §2.1.1. The driving patterns from this transport simulation are deterministic, i.e. they represent a snapshot of a typical day. However, from a power systems perspective, it is important to understand the variability of these patterns. This topic is addressed in §2.1.2.
2.1. Driving patterns

2.1.1 Driving pattern generation

In the following, an agent-based transport simulation, and other alternative sources of driving patterns are described.

Agent-based transport micro-simulation

The driving patterns used in this thesis stem from the agent-based transport micro-simulation tool MATSim [68–71], where each agent is simulated individually. Agents carry out activities, such as working, shopping, sleeping, etc. An agent needs to make, among others, decisions concerning the following [69]:

- The type of activities to be performed.
- The activity starting time and duration.
- The sequence of activities.
- The location where an activity is performed, e.g. where to go shopping.
- The route to take to a particular location, e.g. to work.
- The transport mode, e.g. private car vs. bus.

The set of decisions of an agent is called a plan, comprising the sequence, location and timing of activities to be performed during the day, together with the travel modes and routes that bring the agent from one activity location to the next [71]. An agent keeps track of several alternative plans, which are scored according to the results of the micro-simulation. With a co-evolutionary algorithm [68], the optimal plan for each individual agent is determined. This is done through an iterative process, represented in Fig. 2.1. The algorithm is started with an initial demand, then the simulation is executed and the executed plans are scored according to a utility function. Based on these scores, a replanning process takes place, and a given plan is chosen to be executed at the next iteration. The replanning process involves deleting daily plans with low score, as well as duplicating and modifying daily plans. After convergence, the relaxed demand, comprising an optimal
plan for each agent, is obtained. The plans of different agents affect each other, e.g. through the induced traffic on a particular route.

From the transport simulation, only the trips performed with the transport mode corresponding to passenger cars are of interest here. The relevant outputs from the transport simulation used to model the electricity demand of PEVs are, for each vehicle:

- The departure and arrival times of each trip.
- The parking locations (geographic coordinates), used to map the PEVs to specific network nodes.
- The length and duration of each trip, used to establish the trip energy consumption.
- The activity type (e.g. home or work). This can be relevant when some of the charging parameters are assumed to be activity-type dependent. For example, a scenario can be defined where only home charging is available, or different rated powers could be assigned to different types of locations.

To compute the energy consumption out of the distance driven, a fixed efficiency value, in kWh/km, could be assumed. Since MATSim gives some information on the type of roads that an agent drives on during a given trip, driving-cycle specific efficiency values could also be used, e.g. different values can be defined for urban, rural and highway driving cycles. Moreover, the consumption of auxiliaries, such as heating and air conditioning, is more strongly related to the duration of the trip than to the length of the trip. This consumption is dependent on outdoor temperature, and varies therefore substantially across seasons.
2.1. Driving patterns

Alternative sources of driving patterns

Driving patterns can also be generated with statistical methods, based on data from transport surveys/statistics, such as the “National Household Travel Survey” in USA [72], “Inquérito à mobilidade da população residente” in Portugal [73], “Verkehrserhebung” in Austria [74], and the “Mikrozensus Mobilität und Verkehr” in Switzerland [75]. Some statistical reports of this kind comprise information on individual driving patterns from transport surveys [30, 31, 76]. Others report aggregated statistical data only, e.g. on the distribution of trip lengths. When only aggregated statistical data is available, models need to be developed that generate individual driving patterns that in their aggregated characteristics reproduce the desired aggregated statistical behavior [77]. Such models can be based on Markov chains, see §2.1.2.

Generic vs. PEV-specific driving patterns

In most of the cases, the models to generate driving patterns are based on statistical data of the use of conventional combustion engine vehicles. It can be expected that the driving patterns of PEVs at least partially differ from these. More specifically, the limited range of PEVs imposes constraints on the way they are used. PEV pilot projects can be a source of PEV-specific driving patterns [78, 79]. However, the sample size in pilot projects is typically quite small, making it hard to derive general statistical behavior from this limited number of samples.

The agent-based transport simulation MATSim, whose driving patterns are used as an input to the models in this thesis, builds up on general transport survey statistics. Therefore, PEV-specific patterns could not be considered here.

2.1.2 From deterministic to probabilistic driving patterns

When studying the impact of controlled and uncontrolled charging on power systems, and the role of PEVs as providers of ancillary services, it is relevant to consider the uncertainty related to driving behavior. Therefore, it is of interest to have not only a single driving pattern per vehicle (and maybe per day-type and season), but a set of samples of
driving patterns (also potentially per day-type and season) that characterizes the uncertainty of driving behavior.

First, the relevant literature is briefly surveyed. Then, the model used in this thesis, based on continuous-time non-Markov chains, is presented.

**Literature survey**

A popular model to generate Monte Carlo samples of driving patterns are discrete-state, discrete-time *Markov chains* \cite{27, 77, 78, 80}. In this framework, several states are defined, e.g. a) in movement, b) parked in a residential area, c) parked in an industrial area, and d) parked in a commercial area \cite{77, 80}. The State of Charge (SOC) can also be included in the parametrization of the states \cite{78}. The transition probabilities between the states can be set according to statistical transport data \cite{77, 80} or PEV trial data \cite{78}, see §2.1.1. The transition matrices are typically time-dependent, i.e. the Markov chain is time-inhomogeneous.

In \cite{81}, variables such as home arrival and departure time and travelled distance of a group of commuters are modeled as stochastic variables, and their interdependencies are taken into account with *copula functions*. Instead of assuming the stochastic variables to be Gaussian distributed, as it is commonly done for simplicity \cite{82, 81} finds that other types of distributions, such as the Weibull distribution for the departure time, better match the specific commuter data used in \cite{81}.

Another way to model vehicle charging and discharging is *queuing theory* \cite{83}. The underlying assumption is that the number of charged/discharged vehicles is distributed according to a Poisson distribution, and that the service time (charging) is exponentially distributed.

**Continuous-time non-Markov chains**

In the following, the model used in this thesis is described. As with the Markov chain model, different states are defined here. Specifically, a driving state and four parking states (parked at work, at home, at a leisure location, or at a shopping location) are introduced, depicted in Fig. 2.2 together with the possible state transitions. Defining different parked states allows to set some parameters conditional on the state (e.g. only home charging is available, or a higher rated charging power is installed at commercial locations than at home).
2.1. Driving patterns

In contrast to [77, 78, 80], a non-Markov process is assumed to drive state transitions in this thesis. The reason for this choice is that mobility patterns probably do not fulfill the Markov property, i.e. they are not memoryless. Memorylessness means that the probability of transitioning to a given state depends only on the current state, not on the previous history. However, the time when a vehicle departs from a particular location, i.e. enters the driving state, is typically influenced by the time of arrival at that location, and thus by the time of departure from the previous location. In the proposed model, the sojourn time at a particular state is given by two stochastic variables: the time of departure and the trip duration. These variables determine the transition from a parked state to the driving state, and the transition from the driving state to a parked state, respectively. Note that the correlation between arrival and departure times is therefore taken into account through the stochastic trip duration. Compared with the models in [77, 78, 80], where a single Markov chain is defined for the fleet, here each vehicle is associated with a non-Markov process with different parameters.

It is assumed that, on a particular day, a vehicle is used for a certain number of activities performed in a certain order (e.g. home-work-shop-home), which correspond to the parked states. These activity chains are obtained from the agent-based transport simulation described in §2.1.1 and are assumed to be perfectly known in advance. For a more general model, it would be possible to define a set of potential activity chains for a given vehicle, each with a given probability of being executed. The departure time and duration of each trip between activities are modeled as stochastic variables whose expected values are known, corresponding to the values obtained from the agent-based transport simulation. A distribution with a finite support, e.g. a uniform distribution or a trun-
Chapter 2. Modeling PEVs’ demand flexibility

cated normal distribution, needs to be used to model departure times and trip durations, in order not to alter the activity chains. To account for variations in the energy consumed during each trip, this variable is also modeled as a stochastic variable with a finite support distribution.

Available data on driving patterns typically comes from mobility surveys. With this data, distributions of variables such as departure times, etc. for a fleet can be derived, but not distributions describing the stochastic behavior of each individual vehicle. Data from PEV trials could potentially provide statistics for individual PEVs, if their driving patterns are recorded over time. For demonstration purposes, the stochastic variables mentioned above will be modeled with uniform distributions in the case studies presented in this thesis. In practice, in a centralized control setting, the aggregator would need to collect data from its PEV customers to find appropriate models for their stochastic behavior. In a decentralized setting, a local control device would need to do the same. In both cases, machine learning techniques could be used to model the stochastic behavior in an adaptive way. Moreover, the energy demand depends in practice on factors such as the weather, through the consumption of the heating, ventilating, and air conditioning (HVAC) system. With real data, it would also be interesting to model correlations between the stochastic variables appropriately, e.g. between the trip duration and the trip energy consumption. Nonetheless, the assumptions regarding the distribution of the stochastic variables made here do not affect the validity of the overall approach presented in this thesis.

2.2 From driving patterns to an individual PEV flexible demand model

In the context of decentralized charging optimization schemes, or centralized schemes where a limited number of PEVs are considered, individual representations of the sets of feasible charging profiles are used. These representations can be based on more or less detailed models of the battery charging (and discharging) processes. First, the models commonly used in the literature are briefly surveyed in §2.2.1 and then the linear model used in this thesis is described in more detail in §2.2.2.
2.2. Individual PEV flexible demand model

2.2.1 Literature survey

In some cost minimization problems concerning the charging of PEVs, batteries are modeled with an equivalent circuit model. In many cases, simple linear charging models are used.

The equivalent circuit models are typically composed of an ideal voltage source and an internal resistance, which are both dependent on the SOC of the battery [85, 86]. This type of model is used in [85], where the cost-optimal individual charging schedules of plug-in hybrid electric vehicles are determined with dynamic programming. In this case, the SOC evolution of the battery is also modeled during the driving phase. In [86], where an analogous equivalent circuit model is employed, costs not only include the energy-related costs, but also the costs associated with battery degradation, computed with an electrochemistry-based model of anode-side resistive film formation in lithium-ion batteries. An alternative model for battery degradation is proposed in [87], where both energy capacity and power fade are modeled as a function of temperature, SOC profile, and daily depth of discharge.

In many charging cost minimization problems, simple linear models representing the energy dynamics of the battery are used [28, 32, 88, 89, 91], see next subsection §2.2.2. In [92], both a linear and a quadratic approximation for the battery behavior are tested against a more accurate non-linear state-dependent battery model. The results suggest that the linear approximation is sufficient for the purpose of charging schedule optimization. A linear model is also used throughout this thesis, since it significantly reduces the complexity of the associated optimization problems, without seriously compromising accuracy. This linear model is described in detail in the following.

2.2.2 Linear PEV flexible demand model

The equations that define the set of feasible charging profiles, are determined out of the driving patterns, as well as the characteristics of the PEV batteries and the charging infrastructure [52, 54, 66]. The PEV demand model used here is time-discrete. Therefore, the time-continuous data from the transport simulation needs to be discretized: A PEV is considered to be in a parked state during a given time step only if it is parked for the total duration of that time step, otherwise it is considered to be in a driving state. Each vehicle $v$ has a battery with capacity
Chapter 2. Modeling PEVs’ demand flexibility

$C^V_v$ and efficiency $\eta^V_v$, assumed symmetric for charging and discharging. The battery is operated between two SOC levels, $\text{SOC}^V_v,_{\text{min}} \geq 0$ and $\text{SOC}^V_v,_{\text{max}} \leq 1$, to limit battery degradation. The binary parameter $u^V_v t$ defines the type of state of the vehicle at a particular time step. At each time step $t$, a vehicle is in a driving state, i.e. $u^V_v t = 0$, or in a parked state, i.e. $u^V_v t = 1$. During the driving state, a certain amount of energy $E^{V,\text{cons}}_v t$ is consumed by the PEV, and the maximum charging power $P^{V,_{\text{max}}}_v t$ is set to zero. During the parked states, a maximum available charging power $P^{V,_{\text{max}}}_v t$ is defined, which can be location-dependent. The maximum charging power is equivalent to the minimum of a) the maximum charging power given by the PEV’s power electronics and battery, and b) the maximum charging power of the charging station.

The energy content of a PEV battery at the end of each time step $t$, $E^V_v t$, is determined by the dynamic equation

$$E^V_v t = E^V_v (t-1) + P^V_v t \eta^V_v \Delta t - E^{V,\text{cons}}_v t, \quad \forall v, \forall t, \quad (2.1)$$

where $\Delta t$ is the duration of the time step and $P^V_v t$ the charging power at time step $t$. For simplicity, a linear model is used for the battery dynamics, which are in practice non-linear. However, as discussed in the literature review in §2.2.1 for the type of studies conducted in this thesis, the use of the simple linear model is justified [92].

If a given PEV is not a pure electric vehicle, but a plug-in hybrid, a term to account for fuel consumption can be included in the dynamic equation (2.1). In this case, $E^{V,\text{cons}}_v t$ not only represents the energy being drawn from the battery, but also comprises the part of the energy consumption (from the battery’s perspective), covered by the use of fuel. Considering the energy from fuel $E^{V,\text{fuel}}_v t$, (2.1) becomes,

$$E^V_v t = E^V_v (t-1) + P^V_v t \eta^V_v \Delta t + E^{V,\text{fuel}}_v t - E^{V,\text{cons}}_v t, \quad \forall v, \forall t, \quad (2.2)$$

where $E^{V,\text{fuel}}_v t \leq E^{V,\text{cons}}_v t$.

The upper and lower bounds of the energy content are given by the battery capacity $C_v$ and the SOC bounds

$$C^V_v \text{SOC}^V_v,_{\text{min}} \leq E^V_v \leq C^V_v \text{SOC}^V_v,_{\text{max}}, \quad \forall v, \forall t. \quad (2.3)$$

The charging power of a battery is also bounded. For unidirectional charging the lower bound is equal to zero, i.e.

$$0 \leq P^V_v t \leq P^{V,_{\text{max}}} v t, \quad \forall v, \forall t, \quad (2.4)$$
2.2. Aggregated PEV flexible demand model

whereas with bidirectional charging the lower bound \( P_{vt}^{V,\text{min}} \) can be negative

\[
P_{vt}^{V,\text{min}} \leq P_{vt}^{V} \leq P_{vt}^{V,\text{max}}, \quad \forall v, \forall t. \tag{2.5}
\]

With bidirectional charging, the dynamic equation (2.1) needs to be modified to account for the discharging processes, weighting the charging \( P_{vt}^{V} \) and discharging power \( P_{vt}^{V,-1} \) with the charging and discharging efficiencies, respectively, i.e.

\[
E_{vt}^{V} = E_{v(t-1)}^{V} + (P_{vt}^{V,+}) \eta_{vt}^{V} \Delta t + (P_{vt}^{V,-}) \Delta t / \eta_{vt}^{V} - E_{vt}^{V,\text{cons}}, \quad \forall v, \forall t. \tag{2.6}
\]

Finally, when the above equations are used as constraints in an optimization, e.g. charging cost minimization, it is important to add an extra constraint that ensures that the energy contents at the beginning \((t = 0)\) and end \((t = T)\) of the optimization horizon, typically 24 hours, are equal,

\[
E_{v(t=0)}^{V} = E_{v(t=T)}^{V}, \quad \forall v. \tag{2.7}
\]

This is done to avoid myopic behavior. Otherwise, due to cost minimization, the vehicle would tend to deplete the battery and shift as much charging as possible beyond the optimization horizon, since the costs beyond that point are not taken into account at that stage. Alternatively, a term associated with the final energy content could be included in the objective function of the cost minimization problem \[85\].

The charging power \( P_{vt}^{V} \) is considered a continuous variable here, i.e. it is assumed that charging can not only be on-off controlled but also modulated.

2.3 From driving patterns to an aggregated PEV flexible demand model

When an aggregator needs to centrally coordinate the charging of many PEVs simultaneously, an aggregated representation of the fleet’s demand flexibility may be required to reduce the complexity of the problem. In §2.3.1 different aggregation models proposed in the literature are described, which are classified into virtual battery-type models and task-type models.

\[(P_{vt}^{V})_+ := \max(P_{vt}^{V}, 0) \text{ and } (P_{vt}^{V})_- := \min(P_{vt}^{V}, 0).\]
In this thesis, a virtual battery-type model is used. To derive the parameters describing the virtual battery constraints, a bottom-up approach is adopted, building on the driving patterns and characteristics of individual PEVs. The first step consists of computing extreme trajectories for the power and energy profiles of each vehicle, see §2.3.2. As a second step, this information is aggregated to build the virtual battery model introduced in §2.3.3. Finally, the previous model is extended to take driving pattern uncertainty into account in §2.3.4.

2.3.1 Literature survey and contributions

First, an overview of existing models used to represent the aggregated charging flexibility of PEV fleets is given, based on [52, 53, 67]. These models can be mainly classified into two types:

- Virtual battery-type models, i.e. models based on the aggregation of energy and power constraints over time.
- Task-type models, i.e. models where charging is modeled as a task with a task size, arrival time and deadline.

Virtual battery-type models

In [30], where an aggregator manages the electricity market participation of a PEV fleet, the fleet is modeled as a set of aggregate vehicles, each of them representing a number of vehicles with similar driving patterns. These driving patterns are constructed by clustering historical data. First, different variables are extracted from the historical data, namely vehicle user, hour and day of departure, and driving distance. From these, a 24-h driving pattern for each vehicle user is constructed. Then, the vehicle fleet is partitioned into different types of vehicles (aggregate vehicles). Vehicles are first grouped according to day of departure (weekday or holiday/weekend) and vehicle technology (pure electric vehicle or plug-in hybrid electric vehicle). Second, driving patterns within each of the groups determined in the first step are clustered using the k-means algorithm. Each cluster is represented by a single driving pattern, and weighted according to the number of vehicles within the cluster.
2.3. Aggregated PEV flexible demand model

An algorithm to calculate load shift potentials is proposed in [93]. It is assumed that customers require a full battery by a given deadline. However, there is generally a large number of charging profiles that meet this requirement, as well as other technical restrictions. This paper identifies the load shift potentials, which are defined as the range of all charging curves that meet the customers’ requirements and respect all individual charging and discharging constraints over time.

References [27, 91, 94] represent the aggregated charging flexibility with aggregate power and energy constraints that are derived from individual PEV power and energy constraints.

In [94], it is assumed that the energy in the battery of each vehicle should have a certain value by a given deadline. Based on this condition, two extreme energy trajectories for each vehicle can be derived: the lower trajectory describes the energy content when charging is delayed as much as possible, while the upper trajectory describes the energy content when charging is scheduled as soon as possible. The charging power is defined as a piecewise linear function of the charging priority/urgency. The energy profiles of the individual vehicles and their power demand curves are summed up for an aggregated representation of the fleet’s flexibility. A stochastic version of this model, taking into account the uncertainty in arrival and departure times is proposed in [95]. The resulting optimization problem is formulated as a Markov Decision Process, which is solved with Dynamic Programming.

In [91], an approach for the optimal charging of PEVs, taking into consideration electricity grid constraints (voltage and power), is proposed. The feasible aggregated charging profiles of the fleet are represented by aggregate power and energy constraints. The energy constraints are derived in a similar way as in [94]. For the individual power profiles, it is assumed that PEVs can charge (and discharge) at the maximum rated power whenever they are connected.

In [27], a bidding strategy for a PEV aggregation agent in the electricity market is described. The charging flexibility of the PEV fleet is also represented with aggregate power and energy constraints, but the details on how to parameterize these are not provided in the paper.
Task-type models

In [96], a clustered representation of the flexible demand of a PEV fleet as a queue of tasks is proposed. In this work, charging is controlled centrally by an aggregator, who optimizes the timing of demand. The rate at which vehicles charge is fixed, but charging can be initiated and interrupted by the aggregator. Charging is modeled as a number of serially executed subtasks, where tasks that are similar are clustered for an aggregated representation of the demand of the fleet. The PEVs move from one cluster to the next cluster by charging, until they reach a full charge. The decision variable in this model is the number of PEVs that are allowed to move from one cluster to the next, i.e. to charge. The goal of the aggregator is to buy enough power in the market to serve the PEVs and, at the same time, to follow a 5-minute real time signal from an Independent System Operator.

A similar approach is found in [97], where PEV charging requests are classified into a reduced number of load types. As in the previous paper, it is assumed that the aggregator can interrupt charging, but not affect the charging rate. This approach models the PEV load in more detail, by defining charge profiles where the charging power changes over time (this is the case for the constant-current/constant-voltage charging profile), and not only constant-power profiles. The non-constant power loads are approximately characterized by multiple stages of different power demands, which are SOC-dependent. Load types are characterized by four variables: the earliest charging start time, the latest charging completion time, the required total charging time and the power demand at each charging stage. The aggregator needs to determine, at each time step, how many requests of a certain load type should be served. This can be formulated as a mixed integer program, and further approximated to a linear program for large fleets. Since this optimization problem could be computationally demanding, the authors propose a two-step procedure to solve it. In the first step, the total number of PEVs of each load type to be served is determined, while in the second step the power allocated to each load type is distributed among the charging stages associated with that task. The first step is formulated as an integer linear program in the general case, while the second step is based on the earliest-stage first policy. The method is applied to a load peak minimization problem.

In [98], a model to represent aggregated demand dynamics is proposed,
both for thermostatically controlled loads and for PEVs. Individual load dynamics and aggregated dynamics are based on hybrid dynamical system load models. PEV charging is modeled as a task, characterized by arrival time, task size, and deadline. The control signal envisaged in this framework would activate PEVs with task laxity (slack time) equal or lower to the value of the signal. The hybrid system which characterizes charging has three modes: waiting, charging and complete. The aggregation of loads is based on methods from fluid dynamics, using density functions for the discrete modes of the hybrid motion. In the general case of inhomogeneous loads, clustering can be used to define sets of homogenous aggregate models. In the case of PEVs, it is necessary to model the arrival of PEVs as external flows entering the aggregate model. The model is proposed as an analysis tool and, potentially, for controller design. However, the model is not used for the purpose of optimization.

The same hybrid model described in [98] is used in [99], where it is extended to a stochastic version. A two-step approach is proposed, where the first step represents the energy planning decision (how much energy should be consumed at each time step of a given time horizon) and the second step is the real time charging control. In the second step, a power tracking policy needs to be defined, that allocates the power budget to the vehicles as precisely as possible, given vehicle constraints. To determine the optimal charging profile in the first step, the maximum and minimum consumable energy at each time step for a close-loop trajectory with a predefined policy is estimated. The energy bounds are represented as a function of the previous power schedules. The energy-planning problem can be solved with dynamic programming. The approach is tested in a setup where the charging costs given exogenous prices are minimized.

Contributions of the proposed aggregated model

The model described in this thesis [49] is a virtual battery-type model similar to [27, 91, 94], where the feasible aggregated profiles are defined by a set of aggregate power and energy constraints. The main contributions with respect to the virtual battery-type models described above are the following:
• The aggregation is location-dependent, i.e. at each network node a virtual battery is modeled. To be able to do so, the energy contributions of vehicles arriving and departing from/to the aggregation, potentially from different network locations, are modeled.

• The influence of the energy constraints on the power constraints is taken into account.

• A probabilistic version of the virtual battery constraints, accounting for driving pattern uncertainty, is proposed.

2.3.2 Deriving individual power and energy trajectories

Starting at the individual PEV level, it is possible to define upper and lower trajectories, \( E_{vt}^{V,\text{up}} \) and \( E_{vt}^{V,\text{low}} \), for the energy in the battery of each vehicle \( v \) at time step \( t \). The upper and lower trajectories correspond to immediate charging and maximally delayed charging, respectively. These trajectories are computed without assuming a specific energy content at the beginning of the period considered. As a reference, it is assumed that the battery reaches the highest allowed SOC at some point in time. From the customers’ perspective, this would also be desirable since their chances of not having enough energy in the battery if they need to drive spontaneously, or earlier than planned, are lowered thereby. Moreover, as in the individual flexibility model (see equality constraint (2.7)), it is assumed that the daily energy consumption is recharged within the same day.

The upper trajectory of the energy content is calculated assuming charging starts as soon as the vehicle parks. The lower energy trajectory is calculated assuming charging is deferred as much as possible, given that a) the vehicle should depart with enough energy in the battery for the forthcoming trip, b) the maximum SOC should be reached at some point, and c) the daily energy consumption should be recovered within the same day. The amount of energy that needs to be in the battery before a trip is calculated with foresight, e.g. when there are two consecutive trips with only a short parking break between them, this is considered when computing the required charging during the parking break preceding the two trips. Since it is assumed that the battery reaches the maximum SOC at some point, and that daily energy needs
are charged within the same day, the depth of discharge with respect to the maximum SOC reference cannot be larger than the normalized daily energy consumption.

It is also of interest to compute the lower energy trajectory when conditions b) and c) above are dropped, or when discharging to the network due to Vehicle to Grid (V2G) is allowed. In these cases, the SOC can reach lower values than previously possible. The corresponding lower energy profile is denoted $E_{VT}^{V,\text{low,free}}$, and can be interpreted as the minimum energy that should be in the battery at a given time step $t$ in order not to impact the end-use constraints of the PEV driver.

Figure 2.3 shows how the upper trajectory and the two lower trajectories are determined for a particular vehicle. The upper trajectory $E_{VT}^{V,\text{up}}$ corresponds to the maximum allowed SOC most of the time, except after the trips, when it starts increasing immediately at the maximum predefined charging rate. The vehicle considered in Fig. 2.3 does not use the full available battery capacity for its daily trips. Therefore, the lowest energy content it will reach under the assumptions of attaining full charge and recovering the daily energy, $E_{VT}^{V,\text{low}}$, is much higher than the energy content associated with the minimum SOC. Finally, the lower energy trajectory without these restrictions, $E_{VT}^{V,\text{low,free}}$, corresponds to the minimum SOC most of the time, and increases before the trips to make sure that there is enough energy in the battery before departure.

**Figure 2.3:** Example of the upper and lower energy trajectory computation for an individual vehicle. cons. 1/2: Energy consumption of the first and second trip, respectively.
As a next step, the upper and lower power trajectories of each vehicle, $P_{vt}^{V,\text{up}}$ and $P_{vt}^{V,\text{low}}$, are computed. Instead of simply assuming that the vehicle can charge at maximum power whenever it is plugged in, the fact that the charging power is also constrained by the battery’s energy content is taken into account. For this purpose, the previously calculated energy trajectories are taken into account, which yields

$$P_{vt}^{V,\text{up}} = \max\left(\min\left(P_{vt}^{V,\text{max}}, \frac{E_{vt}^{V,\text{up}} - E_{v(t-1)}^{V,\text{low}}}{\eta V \Delta t}\right), 0\right), \quad \text{(2.8)}$$

$$P_{vt}^{V,\text{low}} = \max\left(\min\left(P_{vt}^{V,\text{max}}, \frac{E_{vt}^{V,\text{low}} - E_{v(t-1)}^{V,\text{up}}}{\eta V \Delta t}\right), 0\right), \quad \text{(2.9)}$$

or without the full charge and daily energy recovery conditions,

$$P_{vt}^{V,\text{up,free}} = \max\left(\min\left(P_{vt}^{V,\text{max}}, \frac{E_{vt}^{V,\text{up,free}} - E_{v(t-1)}^{V,\text{low}}}{\eta V \Delta t}\right), 0\right), \quad \text{(2.10)}$$

$$P_{vt}^{V,\text{low,free}} = \max\left(\min\left(P_{vt}^{V,\text{max}}, \frac{E_{vt}^{V,\text{low,free}} - E_{v(t-1)}^{V,\text{up}}}{\eta V \Delta t}\right), 0\right). \quad \text{(2.11)}$$

If V2G is allowed, the lower bound need not be zero, therefore

$$P_{vt}^{V,\text{up,V2G}} = \max\left(\min\left(P_{vt}^{V,\text{max}}, \frac{E_{vt}^{V,\text{up,free}} - E_{v(t-1)}^{V,\text{low}}}{\eta V \Delta t}\right), -P_{vt}^{V,\text{max}}\right), \quad \text{(2.12)}$$

$$P_{vt}^{V,\text{low,V2G}} = \max\left(\min\left(P_{vt}^{V,\text{max}}, \frac{E_{vt}^{V,\text{low,free}} - E_{v(t-1)}^{V,\text{up}}}{\eta V \Delta t}\right), -P_{vt}^{V,\text{max}}\right). \quad \text{(2.13)}$$

To determine the upper power value at time step $t$ the fact that the vehicle can maximally only charge the difference between the lower energy value at the previous time step $t-1$ and the upper energy value at time step $t$ is considered, see (2.8) (2.10) (2.12). Similarly, if the energy lower bound at time step $t$ is higher than the energy upper bound at the previous time step, this signals inflexible charging demand to be considered in the lower power value, see (2.9) (2.11) (2.13).
2.3. Aggregated PEV flexible demand model

2.3.3 Virtual battery model

Based on the individual extreme power and energy profiles, an aggregated flexibility representation can be derived. The following equations describe the aggregated virtual battery model at each network node \( n \) for the unidirectional charging case (no V2G): the energy dynamics,

\[
E_{nt}^A = E_{n(t-1)}^A + P_{nt}^A \eta_{nt}^A \Delta t + E_{nt}^{A,\text{arr}} - E_{nt}^{A,\text{dep}}, \quad \forall n, \forall t, \tag{2.14}
\]

the energy bounds,

\[
E_{nt}^{A,\text{min}} \leq E_{nt}^A \leq E_{nt}^{A,\text{max}}, \quad \forall n, \forall t, \tag{2.15}
\]

and the power bounds,

\[
P_{nt}^{A,\text{min}} \leq P_{nt}^A \leq P_{nt}^{A,\text{max}}, \quad \forall n, \forall t. \tag{2.16}
\]

The energy content of the virtual battery \( E_{nt}^A \) at a particular node \( n \) and time step \( t \) stands for the aggregation of energy contents of all PEVs plugged in at that node at that time step. The dynamics of this variable, defined by (2.14), depend on the aggregated charging power at a given time step \( P_{nt}^A \), the aggregated charging efficiency \( \eta_{nt}^A \), and the positive/negative energy contributions of arriving/departing vehicles, \( E_{nt}^{A,\text{arr}} / E_{nt}^{A,\text{dep}} \). Here, \( E_{nt}^{A,\text{arr}} \) represents the increase in energy content due to the arrival of PEVs at a given time step, and \( E_{nt}^{A,\text{dep}} \) represents the reduction in energy content due to PEV departures. These terms model how energy is shifted from one time step to the other, and from one network node to the other, through the process of vehicles arriving and departing, potentially from one network location to a different one.

As in the individual PEV model, a constraint relating the energy contents at the beginning and at the end of the optimization period is added to avoid myopic behavior,

\[
E_{n(t=0)}^A = E_{n(t=T)}^A, \quad \forall n. \tag{2.17}
\]

The aggregated parameters \( E_{nt}^{A,\text{arr}}, E_{nt}^{A,\text{dep}}, E_{nt}^{A,\text{min}}, E_{nt}^{A,\text{max}}, P_{nt}^{A,\text{min}}, P_{nt}^{A,\text{max}}, \) and \( \eta_{nt}^A \) are determined out of the individual PEV parameters and trajectories as follows

\[
E_{nt}^{A,\text{min}} = \sum_v u_{vnt}^V E_{vt}^{V,\text{low}}, \quad E_{nt}^{A,\text{max}} = \sum_v u_{vnt}^V E_{vt}^{V,\text{up}}, \quad \forall n, \forall t, \tag{2.18}
\]
\begin{align}
P_{nt}^{A,\min} &= \sum_v u^V_{vnt} P^V_{vt,\text{low}}, \quad P_{nt}^{A,\max} &= \sum_v u^V_{vnt} P^V_{vt,\text{up}}, \quad \forall n, \forall t, \quad (2.19) \\
E_{nt}^A,\text{dep} &= \sum_v u^V_{vn(t-1)} (u^V_{vn(t-1)} - u^V_{vnt}) E^V_{v(t-1),\text{up}}, \quad \forall n, \forall t, \quad (2.20) \\
E_{nt}^A,\text{arr} &= \sum_v u^V_{vnt} (u^V_{vnt} - u^V_{vn(t-1)}) E^V_{v(t-1),\text{up}}, \quad \forall n, \forall t, \quad (2.21) \\
\eta_{nt} &= \sum_v u^V_{vnt} \eta^V_{vt} / \sum_v u^V_{vnt}, \quad \forall n, \forall t, \quad (2.22)
\end{align}

where binary parameter \( u^V_{vnt} \) is equal to one when PEV \( v \) is connected to node \( n \) at time step \( t \), and zero otherwise.

Eqs. (2.18) and (2.19) state that the upper and lower power and energy trajectories of a given vehicle contribute to the aggregated bounds of a particular node when the vehicle is connected to that node during the considered time step. The departure and arrival energy terms are computed by aggregating the energy content of the PEVs at the time of departure (2.20) and arrival (2.21), respectively. The actual energy content of PEV batteries at the time of departure and arrival depends on the problem’s decision variables, i.e. on the aggregated charging profiles \( P_{nt}^A \). However, the way the aggregated charging power is distributed among vehicles is not known a priori. For simplicity, a fixed value is chosen for the energy content of a PEV’s battery at arrival and departure. Here, the upper energy trajectory is used to estimate this value, see (2.20) and (2.21). The aggregated charging efficiency is set equal to the average efficiency of the connected PEVs (2.22).

The upper and lower power and energy bounds with V2G are computed analogously, using the individual power and energy trajectories valid with V2G, i.e. \( P^V_{vt,\text{low},\text{V2G}}, P^V_{vt,\text{up},\text{V2G}}, E^V_{vt,\text{up},\text{V2G}}, E^V_{vt,\text{low},\text{V2G}} \). The energy upper bounds remain the same with V2G. A more general virtual battery model including bidirectional charging (V2G mode) will be introduced later in §4.2.1.

**Possible extensions**

The drawback of using aggregated models to represent the fleet’s demand flexibility is that they do not perfectly represent individual requirements [56]. To improve the performance of aggregated models, a number of smaller aggregations, instead of a single aggregation per
node, could be defined. Clustering methods, such as the k-means algorithm, can be applied to group PEVs with similar driving patterns and characteristics [30]. However, there is a tradeoff between computation time (since the number of optimization variables and constraints increases with the number of aggregations/clusters) and the accuracy of the results.

2.3.4 Accounting for driving pattern uncertainty in the virtual battery model

As explained in §2.3.3, the virtual battery model’s aggregated parameters are computed out of individual PEV driving patterns and characteristics. Driving patterns are subject to uncertainty in practice, i.e. neither the aggregator nor the PEVs can perfectly forecast them. Therefore, the virtual batteries’ parameters are subject to a forecasting error [49, 60, 64], denoted \( \omega \) in the following. Equations (2.14)-(2.16) are recast as

\[
E_{nt}^A = E_{n(t-1)} + P_{nt}^A(\eta_{nt}^A + \omega_{nt}^A)\Delta t \\
+ (E_{nt}^{A,\text{arr}} + \omega_{nt}^{E_{nt}^{A,\text{arr}}}) - (E_{nt}^{A,\text{dep}} + \omega_{nt}^{E_{nt}^{A,\text{dep}}}), \quad \forall n, \forall t, \tag{2.23}
\]

\[
E_{nt}^{A,\text{min}} + \omega_{nt}^{E_{nt}^{A,\text{min}}} \leq E_{nt}^A \leq E_{nt}^{A,\text{max}} + \omega_{nt}^{E_{nt}^{A,\text{max}}}, \quad \forall n, \forall t, \tag{2.24}
\]

\[
P_{nt}^{A,\text{min}} + \omega_{nt}^{P_{nt}^{A,\text{min}}} \leq P_{nt}^A \leq P_{nt}^{A,\text{max}} + \omega_{nt}^{P_{nt}^{A,\text{max}}}, \quad \forall n, \forall t. \tag{2.25}
\]

Note that the constraints describing the virtual battery are later incorporated into different charging optimization problems, see §3.2, §3.3 and §4.2. Due to the uncertainties in the model parameters, the constraints that represent the fleet’s demand flexibility are thus more appropriately formulated as chance constraints in these optimization problems. In the following, the chance constraints and their reformulation into a deterministic equivalent are described. The uncertainty regarding the aggregated charging efficiency is considered negligible here, i.e. \( \omega_{nt}^{\eta^A} = 0 \), which simplifies the reformulation of the chance constraints, as will be discussed below.
Reformulation of stochastic inequality constraints

To ease further explanations, inequality constraints (2.24) and (2.25), where \( E^A_{nt} \) in (2.24) is eliminated using (2.23), are rewritten as generic linear inequality constraints with an uncertain parameter \( \omega_j \),

\[
a_j^\top x + \omega_j \leq b_j, \quad j = 1, \ldots, J. \tag{2.26}
\]

The number of inequality constraints, \( J \), is thus four times the number of nodes multiplied with the number of time steps, \( 4NT \). The vector of optimization variables is defined as

\[
x = (E^A_{n(t=0)}, \forall n; P^A_{nt}, \forall n, \forall t). \tag{2.27}
\]

The random variables \( \omega_j \) model the uncertainty associated with the aggregated fleet representation, and are a function of random variables at the individual PEV level, such as departure times, trip durations and trip energy consumptions, i.e.

\[
\omega_j = q_j(\delta), \tag{2.28}
\]

with \( \delta \in \Delta \) the vector of random variables at the individual vehicle level. The constraints (2.26) are formulated as a joint chance constraint, i.e. they are to be jointly satisfied with at least a specified probability \( 1 - \epsilon \),

\[
P(\delta \in \Delta \mid \max_{j=1, \ldots, J} a_j^\top x + q_j(\delta) - b_j \leq 0) \geq 1 - \epsilon. \tag{2.29}
\]

The approach proposed in [100, 101] is used to reformulate the joint chance constraint. The general idea is to define a robust counterpart of (2.29), where the uncertainty \( q_j(\delta) \) is confined in a hyper-rectangle \( B^q^* \). The set \( B^q^* \) is obtained by solving a random program where a finite number of samples \( K \) of \( \delta \) is extracted [102]:

\[
\begin{align*}
\text{Min}, & \quad \sum_j \left( \tau^\text{max}_j - \tau^\text{min}_j \right) \\
\text{s.t.} & \quad q_j(\delta_k) \in [\tau^\text{min}_j, \tau^\text{max}_j], \quad \forall j, \forall k = 1, \ldots, K.
\end{align*} \tag{2.30a}
\]

\[
\begin{align*}
\times \quad \sum_j \left( \tau^\text{max}_j - \tau^\text{min}_j \right) \\
\text{s.t.} & \quad q_j(\delta_k) \in [\tau^\text{min}_j, \tau^\text{max}_j], \quad \forall j, \forall k = 1, \ldots, K.
\end{align*} \tag{2.30b}
\]

The hyper-rectangle \( B^q^* \) is determined using the Cartesian product of the resulting intervals \( [\tau^\text{min}_j, \tau^\text{max}_j] \), as \( B^q^* := \times_{j=1}^J [\tau^\text{min}_j, \tau^\text{max}_j] \). To ensure that the chance constraint (2.29) holds with the predefined
probability $1 - \epsilon$, a given minimum number of samples $K$ need to be extracted. This number depends on the number of uncertainty functions $q_j(\delta)$, i.e. $J$, and the violation parameter $\epsilon$ according to

$$K \geq \left\lceil \frac{1}{\epsilon e - 1} \left( 2J - 1 + \ln \frac{1}{\beta} \right) \right\rceil,$$  \hspace{1cm} (2.31)

where the confidence parameter $\beta$ represents the probability of constraint (2.29) not holding because the extracted samples are not representative. Since this parameter only affects the number of required samples logarithmically, a low value can be chosen for it. Note that, although the dimension of $\delta$ is very large (several stochastic variables per vehicle), this does not have an impact on the number of scenarios to be extracted. The number of samples to be extracted does thus not depend on the number of vehicles in the aggregation.

Finally, with the definition $q(\delta) := (q_1(\delta), \ldots, q_J(\delta))$, (2.29) can be formulated as

$$\max_{j=1,\ldots,J} \max_{q(\delta) \in B^q \cap q(\Delta)} a_j^\top x + q_j(\delta) - b_j \leq 0.$$  \hspace{1cm} (2.32)

Because of the structure of the constraints, this can be further simplified to

$$a_j^\top x \leq b_j - \tau_j^{\text{max}} \forall j = 1, \ldots, J.$$  \hspace{1cm} (2.33)

In conclusion, the inequality constraint is tightened by a margin $\tau_j^{\text{max}}$ obtained by considering different driving pattern scenarios in problem (2.30). Because finally only the $\tau_j^{\text{max}}$ values need to be computed, and not the $\tau_j^{\text{min}}$ values, i.e. the number of optimization variables in problem (2.30) is halved, the number of samples to be extracted can be reduced to

$$K \geq \left\lceil \frac{1}{\epsilon e - 1} \left( J - 1 + \ln \frac{1}{\beta} \right) \right\rceil.$$  \hspace{1cm} (2.34)

The simplification from (2.32) to (2.33) is only possible if the uncertainty enters the inequality via additive terms, as in (2.26). This is the case because the uncertainty related to the aggregated charging efficiency was neglected, i.e. $\omega^\eta_{nt} = 0$. Otherwise, (2.26) would have an additional term consisting of a product of decision variables and stochastic variables. This type of situation, and the corresponding reformulation of the joint chance constraint, is discussed later in §4.2.1.
Using the detailed notation again, the general inequality (2.33) corresponds to the energy constraints

\[ E_{nt}^{A,\min} + \max_k \left( \omega_{knt}^{E_{A,\min}} + \sum_{\tau=1}^t \left( \omega_{knt}^{E_{A,\dep}} - \omega_{knt}^{E_{A,\arr}} \right) \right) \]
\[ \leq \sum_{\tau=1}^t \left( P_{nt}^A \eta_{n\tau} A \Delta t + E_{nt}^{A,\arr} - E_{nt}^{A,\dep} \right) \]
\[ \leq E_{nt}^{A,\max} + \min_k \left( \omega_{knt}^{E_{A,\max}} + \sum_{\tau=1}^t \left( \omega_{knt}^{E_{A,\dep}} - \omega_{knt}^{E_{A,\arr}} \right) \right), \quad \forall n, \forall t, \]

(2.35)

and the power constraints

\[ P_{nt}^{A,\min} + \max_k (\omega_{knt}^{P_{A,\min}}) \leq P_{nt}^A \leq P_{nt}^{A,\max} + \min_k (\omega_{knt}^{P_{A,\max}}), \quad \forall n, \forall t, \]

(2.36)

where \( \omega_{knt}^{E_{A,\min}} \) corresponds to the \( k \)-th extracted sample of the random variable \( \omega_{j}^{E_{A,\min}} \). It is only necessary to extract samples of these variables, which in this case is achieved by generating different samples of driving patterns for each vehicle, see \( \S 2.1.2 \). For this purpose, departure and arrival times, and trip energy consumptions are modeled as random variables, represented by the vector of random variables \( \delta \).

For each of the samples, each comprising driving pattern information for each PEV, the corresponding values of the aggregated parameters are computed, e.g. a \( k \)-th sample of the energy lower bound is obtained, from which the corresponding \( \omega_{knt}^{E_{A,\min}} \) can be computed

\[ E_{knt}^{A,\min} = E_{nt}^{A,\min} + \omega_{knt}^{E_{A,\min}}, \]

and analogously for the other parameters. The values of \( \omega_{j} \) are therefore not directly sampled, but obtained indirectly from the aggregation of individual driving patterns, as represented by (2.28).
2.3. Aggregated PEV flexible demand model

Reformulation of stochastic equality constraints

With uncertainty in the evolution of the energy content $E_{nt}^A$, the equality constraint (2.17) cannot be satisfied for several possible outcomes of the uncertain variables. Substituting (2.23) into (2.17) leads to

$$\sum_t \left( P_{nt}^A \eta_{nt}^A \Delta t + E_{nt}^{A, \text{arr}} + \omega_{nt}^{E_{nt}^A, \text{arr}} - E_{nt}^{A, \text{dep}} - \omega_{nt}^{E_{nt}^A, \text{dep}} \right) = 0, \quad \forall n. \quad \text{(2.37)}$$

Using the median to minimize the mean absolute value of the left hand side of (2.37), i.e. the magnitude of the constraint violation, yields

$$\sum_t \left( P_{nt}^A \eta_{nt}^A \Delta t + E_{nt}^{A, \text{arr}} - E_{nt}^{A, \text{dep}} \right) = \text{med} \sum_t \left( \omega_{nt}^{E_{nt}^A, \text{dep}} - \omega_{nt}^{E_{nt}^A, \text{arr}} \right), \quad \forall n. \quad \text{(2.38)}$$

The median is estimated out of the $K$ samples extracted to reformulate the inequality constraints.

Impact of aggregation size

As mentioned above, the parameters describing the flexibility of the virtual battery are subject to uncertainty. Since these parameters result from the aggregation of parameters at the individual vehicle level, it is expected that they become better predictable with an increasing aggregation size. Figure 2.4 illustrates this: It shows the extreme values and mean of the upper and lower energy bounds for an aggregation of 100 PEVs (Fig. 2.4a) and an aggregation of 1000 PEVs (Fig. 2.4b).

The extreme values are much closer to the mean with the larger fleet, which implies that the difference between the results of the deterministic problem formulation and that of the stochastic problem formulation will be smaller for the larger aggregation. Note that it is assumed that there is no correlation between the deviations from the expected driving patterns of different vehicles, i.e. each vehicle is treated independently.

If this assumption is not valid – e.g. if a strong delay in the arrivals of many vehicles due to an unexpected traffic congestion occurs – then the improvement in the predictability of the model parameters from increasing the fleet size would be less pronounced.
Chapter 2. Modeling PEVs’ demand flexibility

Figure 2.4: Uncertainty in the upper and lower energy bounds ($E_t^{A,\text{max}}$ and $E_t^{A,\text{min}}$) of the virtual battery, for different aggregation sizes (obtained from 1000 samples). The energy content of the virtual battery is normalized by the total fleet capacity.
2.4 Concluding remarks

The focus of this chapter was on models for PEV demand flexibility that can be used in optimization problems harvesting this flexibility.

First, deterministic and stochastic models to generate driving patterns were described. Because of the current limited penetration of PEVs, these models are typically based on statistical data from drivers of conventional vehicles. Moreover, there are rarely available statistics for the variability in the driving patterns of individual drivers. Therefore, further developments of driving pattern models should better capture the PEV-specific driving behavior, and the uncertainty related to individual PEV driving patterns.

Second, models representing individual PEV charging flexibility were discussed. Although battery charging and discharging dynamics are nonlinear, linear representations are considered sufficient in the context of charging scheduling for cost minimization \[92\].

Third, aggregated representations of charging flexibility were outlined. A model for the aggregated flexibility of a PEV fleet as a set of probabilistic time-varying power and energy constraints, reformulated using a scenario-based robust approach, was introduced. An important characteristic of PEV aggregations is that their flexibility becomes better predictable when the number of PEVs in the aggregation increases.
Chapter 3

Charging cost minimization
Chapter 3. Charging cost minimization

The focus of this chapter is on charging control approaches for cost optimization. The goal is to use the charging (and potentially discharging) flexibility of PEVs to minimize the cost of procuring the electricity for the PEVs. As discussed in the Introduction (§1), this cost minimization problem could be considered from the perspective of an energy supplier, or from the perspective of a PEV aggregator.

Charging control approaches can be characterized along the following three dimensions:

- **Decision-making**: Decisions can be taken by individual PEVs (*decentralized* control) or by a central agent (*centralized* control), typically a PEV aggregator.
- **Communication**: Some approaches rely on *bidirectional* communication, whereas others are based on the *unidirectional* top-down broadcast of prices or control signals.
- **Objective**: A decision-making agent (aggregator or PEV) can act in a selfish/*strategic* way, i.e. minimize its charging costs only, or in a *cooperative* way, maximizing social welfare.

Note that the definition of decentralized/centralized control here is only based on who is (are) the decision-making agent(s), not on whether information between agents is shared or not. According to other definitions, decentralized control refers to an approach which does not rely on communication [105]. According to this alternative definition, the approaches referred to as “decentralized” here, would be considered “distributed”, since PEVs communicate with a coordinating agent. In both the centralized and decentralized approaches described here, a PEV aggregator acts as an intermediary agent between the vehicles and other entities, such as energy providers, power markets and system operators [21, 22, 24–26]. In the decentralized approaches, the aggregator has simply a coordinating role, whereas in the centralized approaches, it directly controls PEV charging.

First, the literature on charging control approaches is reviewed and categorized along the dimensions above in §3.1. Then, specific models for the different types of approaches are developed. The direct-control, centralized schemes are described in §3.2 and §3.3, where in §3.2 charging is scheduled so that social welfare is maximized, whereas in §3.3 a strategic bidding approach for a PEV aggregator is introduced. Decentralized
approaches based on bidirectional communication are presented in §3.4 and §3.5. In §3.4 PEVs cooperate to schedule charging in a way that is socially optimal, whereas in §3.5 PEVs compete against each other and other market participants. In §3.6 a framework where each PEV optimizes its charging schedule given exogenous prices is presented. The PEVs therefore act in a selfish way in this case. However, their behavior cannot be considered strategic, since prices are exogenous and can therefore not be influenced by them. Within this framework, a method to determine the optimal prices to be broadcast is described. An overview of the different types of approaches described in this chapter is given in Fig. 3.1. Hierarchical control, using a combination of centralized and decentralized approaches is discussed in §3.7. Some theoretical results are derived in §3.9 for a simplified charging cost optimization problem. Then, the results of the different methods are compared and discussed in §3.9. Specifically, supply and demand bid data from the Swiss day-ahead electricity market, is used to evaluate the different approaches. Finally, some concluding remarks are given in §3.10.

Vehicle to Grid (V2G) is not considered in the models developed in this chapter because the arising additional battery degradation costs are typically too high to be compensated by price arbitrage only [30, 62]. Although battery costs are expected to decrease [106], the spread between peak and off-peak prices is also decreasing due to the increasing penetration of Renewable Energy Sources (RES) [107], which makes arbitrage less profitable. The use of V2G is more attractive in the case of ancillary services, and will therefore be discussed in the next chapter, §4.

3.1 Literature survey and contributions

Different types of approaches for PEV charging management have been proposed. According to the “Smart Energy Management Matrix” in [108, §3], these approaches can be divided into categories, depending on a) whether charging decisions are taken locally by individual vehicles or by a central agent and b) whether bidirectional or unidirectional communication with the PEVs is needed. Here, when appropriate, a further dimension is considered, namely whether decisions are strategic or cooperative (welfare maximizing) [51].
Chapter 3. Charging cost minimization

3.1.1 Centralized control, unidirectional communication

The demand response systems that have been first deployed (and are in use in many countries, such as Switzerland and Australia) are based on centralized control and unidirectional top-down communication. They usually take the form of ripple control [109], whereby some types of devices (e.g. hot water boilers) in a certain area can be switched on/off remotely. With ripple control, a frequency signal (typically in the range of 150-1350 Hz) [109], which indicates if the devices participating in the program should remain switched off, or are allowed to consume power, is injected into the distribution grid. Most of the times, the goal is to avoid consumption from these devices during peak times, i.e. peak-shaving.

The main advantage of these schemes lies in their simplicity, but for this very reason these schemes have many limitations. First, consumer preferences cannot be taken into account, since there is no information from the customer to the central agent activating the remote control, which can lead to acceptance problems. Second, the reaction of the devices to the control signal is largely dependent on the state of each of the devices, which is not known by the central agent, but could
potentially be estimated. Therefore, the response cannot be optimally shaped and might be largely uncertain.

In the specific context of PEV charging management, an approach that would enter this category is the Additive-Increase Multiplicative-Decrease control method [110]. In this framework, the use of a common resource (e.g. distribution transformer) is managed in the following way: Each PEV increases the charging power by a fixed additive amount until congestion occurs. In this case, a signal is broadcast, in response to which each PEV decreases its consumption by a multiplicative factor. Although this type of approach does not ensure that charging deadlines are respected, it can be used effectively to prevent distribution transformers from overheating [110].

3.1.2 Centralized control, bidirectional communication

As in the previous schemes, decisions are taken by a central agent. However, in this case, the central agent can have access to information on consumer preferences and device status through bidirectional communication.

Many approaches to charging control proposed so far consider a central agent, typically a PEV aggregator, directly controlling vehicle charging. In [27, 32, 49, 58], a self-scheduling aggregator aims at minimizing the charging costs of the PEV fleet when buying electricity in the spot market. The aggregator can therefore be considered a strategic agent. In some of the self-scheduling problems, the aggregator is also considered to sell frequency control reserves [27, 29]. In other approaches, the charging of the PEV fleet is scheduled within a Unit Commitment type of problem [111, 113], or an Optimal Power Flow (OPF) problem [18, 59, 61, 62]. In these cases, we can therefore speak of a welfare-maximizing use of the PEVs’ flexibility, in the sense that the system costs, not the private charging costs, are considered.

This type of centralized direct control relies on bidirectional communication between the aggregator, and PEVs, which need to communicate their energy requirements to the aggregator, and receive control signals from it. The advantage of this type of approach lies in its potential to achieve optimal outcomes, since the aggregator has knowledge of the needs of all the considered individual PEVs and can coordinate
their actions. Moreover, the uncertainty related to stochastic PEV behavior can be better managed when pooling a large number of PEVs [56]. However, scalability can become a problem, since the aggregator’s scheduling task typically becomes more complex, and even intractable, with an increasing fleet size. To overcome this problem, aggregated representations of the fleet’s constraints can be used in the aggregator’s optimization problem [27, 29, 30, 49, 58, 91], see also §2.3. However, these approximations entail errors and can over- or underestimate the available flexibility to a certain extent [56, 114]. Another disadvantage of this type of centralized direct control schemes is that they require a rather advanced communication infrastructure, since they typically rely on quasi real-time bidirectional communication. Moreover, user privacy can be an issue, because PEV users need to share private information, e.g. on the timing of their trips, with the aggregator. This type of framework may also suffer from acceptance problems, because customers might not want that an external party manages their devices. However, this issue can be solved by allowing users to manually override the central decisions (at the cost of reducing the predictability of the PEV’s reaction).

3.1.3 Decentralized control, unidirectional communication

This type of approach typically features PEVs minimizing costs based on exogenous price signals (Time of Use (TOU) tariffs) communicated to them [59, 85–87]. The main advantages of this approach are that it has low communication requirements, and that privacy and autonomy can be guaranteed. Moreover, more detailed battery models can be used [85, 87] than when optimizing the charging of a large number of vehicles centrally. However, a complex battery model results in higher requirements for the local intelligence. Possibly, the most important drawback is that, because the impact of PEV demand on prices is not taken into account, undesirable outcomes can be induced, e.g. avalanche effects, due to the synchronization of demand [16, 18]. Note that this undesirable effect is also possible in the centralized approach if the aggregator is regarded as a price taker as in [27, 28, 31, 32]. Because assuming exogenous prices leads to a strong concentration of charging during few hours, this type of strategy is probably only suitable at low PEV penetration levels [16, 18]. In principle, acceptability for such a program
could be high, since customer privacy and autonomy are not an issue, but it could be problematic to expose customers to high price volatility. As with centralized control and unidirectional communication, the response cannot be optimally shaped and might be largely uncertain.

In this context, an important question is how to setup the price signals broadcast to the vehicles optimally, which can be addressed using complementarity modeling [115–117].

### 3.1.4 Decentralized control, bidirectional communication

Several charging control approaches based on decentralized control and bidirectional communication have been proposed. Although they rely on local optimization, an iterative feedback process [54, 88, 89, 118, 119] or a bidding process [90, 108] is introduced, which contributes to overcoming the load synchronization problems associated with the open-loop characteristic of the decentralized control approaches with unidirectional communication. However, the communication requirements still remain high as in the centralized approaches with bidirectional communication. Still, compared with the later approaches, scalability, autonomy and privacy are no longer an issue.

In the approaches using an iterative feedback process [54, 88, 89, 118, 119], the vehicles receive updated information from a central agent (the aggregator) at each iteration, which can be interpreted as a control signal. In [88], an approach based on non-cooperative mean field games is proposed. The cost function of individual PEVs includes the cost of charging over a given period of time, but also a quadratic term penalizing deviations from the fleet’s average charging strategy, communicated by the central agent. For a simplified problem setup (no upper bound on the charging power), the authors show that, for a homogenous PEV population, the solution converges to an almost-Nash equilibrium which nearly flattens the electricity demand valleys. The main drawback of the feedback iteration proposed in [88] is that convergence is guaranteed if the additional penalty term, which is a perturbation to the individual cost minimization problem, is chosen large enough. This limitation has been solved in [118], and more generally in [120] in the presence of any convex charging constraint, including e.g. charging rate bounds and intertemporal energy constraints, via mean field game approaches with specific feedback iterations of guaranteed convergence.
Chapter 3. Charging cost minimization

Based on a global optimization approach rather than game theory, but similar in the solution structure, the work in [89] considers a cost function for individual vehicles consisting of a term accounting for the cost of charging given a price signal which is broadcast to the vehicles, and a term penalizing the deviation from the individual charging decisions in the previous iteration. Convergence is guaranteed for strictly convex objective functions, and does not require homogeneity of the PEV fleet. The convergence rate of this approach however decreases linearly as the fleet size grows, making the approach more suitable for small/moderate population sizes, rather than for large fleets [118].

In [121], a more general approach is proposed to coordinate distributed generators, storage and loads, among other resources, using decentralized optimization. It is based on the Alternating Direction Method of Multipliers (ADMM), and therefore also relies on an iterative feedback process to determine the optimal schedules of the distributed resources. As with the decentralized approaches [88, 89, 118], the approach proposed in [121] is an iterative approach, where the different devices connected to the network solve local problems in parallel and exchange some simple messages to coordinate their actions. However, in this context, PEVs are not considered as competing agents, but cooperate to minimize a common cost function. This approach only requires convexity of the problem to be solved. The approach proposed in [121] can be simplified to represent the problem faced by an aggregator coordinating PEV charging without considering network power flows [119]. This framework is further extended to a stochastic formulation in [54] to take driving pattern uncertainty into account.

An alternative non-cooperative decentralized approach relying on bidirectional communication is based on multi-agent systems and market-based control (also called transactional control). In this framework, agents compete on a market for a resource, which they need as an input to their local control problem. An application of this concept in power systems, with the purpose of balancing demand and supply in clusters of distributed energy resources, is the tool called PowerMatcher [90, 108]. In the PowerMatcher setup, the so-called local device agents communicate their bids to the auctioneering agent, which determines the equilibrium price based on the bids, and communicates it to the local device agents. Moreover, concentrator agents can be defined as intermediaries between devices and the auctioneering agent, aggregating the bids of a group of devices and communicating the price received
from the auctioneering agent to them. In the context of PEV charging scheduling, this type of approach has been used in [55, 94, 122, 123]. Compared with the iterative approaches, market-based control has the advantage of being based on a one-shot auction. However, the intertemporal constrains of the vehicles are no longer handled explicitly, and this aspect must therefore be integrated into the bidding behavior of the vehicles, e.g. with machine learning based heuristics [55, 124, 125], which leads to suboptimal results.

### 3.1.5 Comparison of the different approaches

Table 3.1 gives an overview of the advantages (+/++) and disadvantages (−) of the different types of approaches. Regarding optimality, i.e. how efficiently the available demand flexibility is used to minimize a given cost function, the approaches based on bidirectional communication have the potential to perform best. As discussed in §3.1.4 decentralized iterative feedback approaches have an advantage in this respect compared with one-shot approaches (market-based control). Bidirectional communication is also typically needed to reduce the uncertainty in the reaction of PEVs to the control signals. Privacy issues mainly arise in the centralized approaches with bidirectional communication, since consumer preferences and requirements need to be communicated to the aggregator. The consumers’ autonomy is mainly guaranteed in the decentralized approaches. In this context, it can be argued that, in decentralized iterative approaches, PEVs do partially give up their autonomy by considering cost terms that are not directly related to their private costs. Simplicity is one of the key advantages of the approaches based on signal broadcast (unidirectional communication), not only in terms of the complexity of the scheme itself, but also in terms of the required communication infrastructure. Decentralized approaches are typically scalable in terms of computational complexity, since the computation burden can be shared among the different participants. Whether scalability in terms of the communication infrastructure is also given for decentralized approaches with bidirectional communication, depends on the specific setup of the scheme: For instance, if the aggregator-to-PEV communication consists of broadcasts (e.g. price signal) and the information that the aggregator needs consists of aggregated fleet values (e.g. aggregated charging schedule or aggregated bids), then in principle a single aggregator could serve as a coordinator for a
large fleet with an appropriate communication infrastructure.

**Table 3.1:** Comparison of the advantages and disadvantages of the different types of charging management approaches.

<table>
<thead>
<tr>
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<th>cen.(^1) unidir.</th>
<th>cen. bidir.(^4)</th>
<th>dec.(^2) unidir.</th>
<th>dec. bidir. one-shot</th>
<th>iterative</th>
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<tbody>
<tr>
<td>optimality</td>
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<td>uncertainty in reaction</td>
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<td>privacy</td>
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<tr>
<td>scalability</td>
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\(^1\) cen.: centralized control, \(^2\) dec: decentralized control, \(^3\) unidir.: unidirectional communication, \(^4\) bidir: bidirectional communication.

### 3.1.6 Contributions of the proposed charging scheduling models

In the next sections, different charging scheduling models related to the different possible configurations (centralized/decentralized control, unidirectional/bidirectional communication, welfare maximizing/strategic decision-making) are presented. The contributions are the following:

- A strategic bidding strategy for a PEV aggregator, where the aggregator is modeled as a price-maker and the impact of the aggregator’s bids on prices is taken into account using complementarity modeling (§3.3).

- A scalable and flexible decentralized approach, accounting for driving pattern uncertainty, where PEVs cooperatively solve a common optimization problem by computing local optimization problems in parallel (§3.4), with an aggregator as a coordinating entity.

- An individual bidding strategy, based on reinforcement learning, for competing PEVs in a market-based control context (§3.5).
3.1. Social welfare maximizing centralized scheduling

- A model to determine TOU tariffs optimally, even in the absence of detailed information on PEV driving behavior (§3.6).
- A hierarchical approach to charging scheduling combining the advantages of the centralized and decentralized approaches (§3.7).

3.2 Social welfare maximizing centralized scheduling of PEVs

In this case, the goal is to find the aggregated charging schedule for a PEV fleet that maximizes social welfare, which would represent the optimal use of charging flexibility from a system perspective. The general idea is that the aggregator would submit the constraints that describe the fleet’s charging flexibility to the market operator, and the operator would clear the market taking these into account\(^1\). This is modeled by introducing the virtual battery equations described in [2.3] into a standard simplified version of the OPF problem, a DC OPF formulation,

\[
\begin{align*}
\text{Max.} & \quad \Phi_{WN}^{\text{c}} \sum_{t=1}^{T} \left( \sum_d c_{dt}^D P_{dt}^D - \sum_s c_{st}^S P_{st}^S \right) \\
\text{s.t.} & \quad \sum_d P_{dt}^D + \sum_n P_{nt}^A = \sum_s P_{st}^S, \quad \forall t, \quad (3.1a) \\
& \quad 0 \leq P_{dt}^D \leq P_{dt}^D, \quad \forall t, \forall d, \quad (3.1b) \\
& \quad 0 \leq P_{st}^S \leq P_{st}^S, \quad \forall t, \forall s, \quad (3.1c) \\
& \quad \left| \sum_n D_{nl} \left( \sum_{s \in \Omega_n^S} P_{st}^S - \sum_{d \in \Omega_n^D} P_{dt}^D - P_{nt}^A \right) \right| \leq P_{L}^{\text{max}}, \forall t, \forall l, \quad (3.1d) \\
& \quad \Phi_{WN}^{\text{c}} = \{ P_{st}, \forall s, \forall t; P_{dt}, \forall d, \forall t; P_{nt}^A, \forall n, \forall t; E_{n(t=0)}^A, \forall n \} \quad (3.2)
\end{align*}
\]

\(^1\)This type of approach is not compatible with the self-scheduling based markets present in most European countries, but could be introduced in a central dispatch scheme, in particular in a unit commitment problem [111,113].
The goal of the DC OPF (3.1a) is to maximize the consumer and producer surplus, given the demand and supply bid prices $c_{dt}^D$ and $c_{st}^S$, respectively. The power balance in the system (demand equals supply) is enforced by (3.1b). The lower and upper bounds of demand (3.1c) and supply (3.1d) bid volumes, as well as the limits on line and transformer loading $P_{L,max}^l$ (3.1e), are also enforced. Power flows are calculated by means of power transfer distribution factors (PTDFs) $D_{nl}$, taking into account the demand and supply bids that correspond to a given node $n$, $d \in \Omega_n^D$ and $s \in \Omega_n^S$, respectively, and the aggregated demand from PEVs at that node $P_{nt}^A$. Finally, (3.1f) stands for the virtual battery constraints (2.14)-(2.17), which describe the set of feasible aggregated charging schedules. Note that (3.1) is a multiperiod OPF, since the dynamic equation of the virtual battery (2.14) couples the different time steps. The scheme is applied day-ahead.

Problem (3.1) corresponds to the clearing of a market with nodal prices, also known as Locational Marginal Prices (LMPs). LMPs are used in, e.g. the PJM Interconnection and ERCOT. In most European power markets, supply and demand bids are matched without consideration of power flows and internal congestions (copper-plate model). To represent this type of market clearing, constraint (3.1e) can be removed and the index $n$ can be dropped, since all the nodes can be aggregated to a single node. Therefore, a single virtual battery is needed to represent the flexible demand of the fleet. Problem (3.1) becomes

$$\text{Max.} \quad \Phi_{WC}^{\text{WC}} = \sum_{t=1}^{T} \left( \sum_d c_{dt}^D P_{dt}^D - \sum_s c_{st}^S P_{st}^S \right)$$

s.t.

$$\sum_d P_{dt}^D + P_{t}^A = \sum_s P_{st}^S, \quad \forall t,$$

$$0 \leq P_{dt}^D \leq P_{dt,\text{max}}^D, \quad \forall t, \forall d,$$

$$0 \leq P_{st}^S \leq P_{st,\text{max}}^S, \quad \forall t, \forall s,$$

$$E_{t}^A = E_{(t-1)}^A + P_{t}^A \eta_{t}^A \Delta t + E_{t,\text{arr}}^A - E_{t,\text{dep}}^A, \quad \forall t,$$

$$E_{t,\text{min}}^A \leq E_{t}^A \leq E_{t,\text{max}}^A, \quad \forall t,$$

$$P_{t,\text{min}}^A \leq P_{t}^A \leq P_{t,\text{max}}^A, \quad \forall t,$$

$$E_{(t=0)}^A = E_{(t=T)}^A,$$

with decision variables

$$\Phi_{WC}^{\text{WC}} = \{P_{st}^S, \forall s, \forall t; P_{dt}^D, \forall d, \forall t; P_{t}^A, \forall t; E_{(t=0)}^A\}.$$
The energy content of the virtual batteries at time zero, $E^{A}_{n(t=0)}$, in both problems (3.1) and (3.3) is considered an endogenous variable. As the market clearing of the day-ahead market takes place hours before $t = 0$ actually occurs, the aggregator has the possibility of driving the energy content to the desired value up to that time. Note that because of the equality (2.17)/(3.3h), and because $E^{A}_{n(t=T)}$ is bounded through equation (2.15)/(3.3f), $E^{A}_{n(t=0)}$ cannot take arbitrary values. $E^{A}_{n(t=0)}$ is chosen to be endogenous to keep results as general as possible. However, the proposed problem formulation is also valid for a fixed $E^{A}_{n(t=0)}$.

To take driving pattern uncertainty into account, constraint (3.1f) in problem (3.1) and constraints (3.3e)-(3.3h) in problem (3.3), can be replaced by their probabilistic counterparts, as described in §2.3.4.

3.3 Strategic centralized scheduling of PEVs

In §3.2, the demand of the fleet is scheduled in a way that is optimal for the system. In this section, the aggregator is considered to behave strategically. The goal of the aggregator is to find a bidding strategy for the day-ahead market that minimizes the cost of purchasing the energy for charging while satisfying PEV driver end-use constraints, modeled as constraints on a virtual battery. The electricity price considered in the aggregator’s cost function is the outcome of a market clearing process, which depends on the aggregator’s demand bids, as well as the other market participants’ supply and demand bids. This market clearing process is explicitly modeled.

In contrast to other centralized scheduling strategies that either consider exogenous market prices [27, 28, 31, 32], or define prices as a linear or non-linear function of the load [30, 91], the strategic bidding here [49] explicitly models the market-clearing using complementarity modeling [126]. The problem formulation is inspired by the bidding strategy for a generating company in [127]. The problem formulated in the following is based on a copper-plate type of market clearing. However, it is possible to formulate the market clearing problem as a DC-OPF.

\[\text{In that case, the individual upper and lower energy and power trajectories described in } \text{(2.3.2) need to be recomputed using the fixed individual initial energy content as the starting point.}\]
(see problem (3.1)) as in [127], without changing the type of problem to be solved: A Mixed Integer Linear Programming (MILP) problem [128], as formulated later in §3.3.3.

The aggregator’s bidding strategy is formulated as a bilevel problem in §3.3.1. The upper level problem corresponds to the aggregator’s cost minimization, while the lower level problem corresponds to the market clearing process, i.e. the maximization of supplier and consumer surplus, see Fig. 3.2. These problems are interlinked, since the market clearing depends on the aggregator’s bidding decisions, while the aggregator’s optimization problem depends on the market outcomes. In practice, the aggregator does not know the bids of other market participants ex-ante. To address the corresponding uncertainty, the problem is formulated as a stochastic problem in §3.3.2. Mathematically, the bilevel problem corresponds to a Mathematical Problem with Equilibrium Constraints (MPEC) [129], which can be formulated as a MILP problem, see §3.3.3.

**Figure 3.2:** Bilevel structure of the strategic bidding problem.
3.3. Strategic centralized scheduling

3.3.1 Bilevel model with perfect information

In the upper level problem, the aggregator minimizes the costs of purchasing electricity subject to the virtual battery constraints,

\[
\text{Min. } \Phi_{UL}, \Phi_{LL} \sum_t \lambda_t P_t^A \Delta t \tag{3.5a}
\]

s.t. \[
E_t^A = E_{(t-1)}^A + P_t^A \eta_t^A \Delta t + E_t^A,\text{arr} - E_t^A,\text{dep}, \quad \forall t, \tag{3.5b}
\]

\[
E_t^A,\text{min} \leq E_t^A \leq E_t^A,\text{max}, \quad \forall t, \tag{3.5c}
\]

\[
P_t^A,\text{min} \leq P_t^A \leq P_t^A,\text{max}, \quad \forall t, \tag{3.5d}
\]

\[
E_{(t=0)}^A = E_{(t=T)}^A, \tag{3.5e}
\]

\[
\text{(3.7f), } \forall t, \tag{3.5f}
\]

with decision variables for the upper level problem

\[
\Phi_{UL} = \{c_t^A, \forall t; E_{(t=0)}^A\}, \tag{3.6}
\]

where \(c_t^A\) is the price of the aggregator’s bid at time step \(t\). The market clearing price \(\lambda_t\) and the accepted volume of the aggregator’s bid \(P_t^A\), stem from the solution of the market clearing problem \((3.7)\) for time step \(t\)

\[
\text{Max. } \Phi_{LL}^t \sum_d c_{dt}^D P_{dt}^D + c_t^A P_t^A - \sum_s c_{st}^S P_{st}^S \tag{3.7a}
\]

s.t. \[
\sum_d P_{dt}^D + P_t^A = \sum_s P_{st}^S : \lambda_t, \tag{3.7b}
\]

\[
0 \leq P_{dt}^D \leq P_{dt}^{D,\text{max}}, \quad \forall d, \tag{3.7c}
\]

\[
0 \leq P_{st}^S \leq P_{st}^{S,\text{max}}, \quad \forall s, \tag{3.7d}
\]

\[
0 \leq P_t^A \leq P_t^{A,\text{max}}, \tag{3.7e}
\]

with decision variables for the lower level problems

\[
\Phi_{LL}^t = \{\Phi_{LL}^t, \forall t\}; \quad \Phi_{LL}^t = \{P_{st}^S, \forall s; P_{dt}^D, \forall d; P_t^A\}. \tag{3.8}
\]

In the lower level problem \((3.7)\), the total surplus of the market participants is maximized \((3.7a)\). Note that, compared with \((3.3a)\), the objective function \((3.7a)\) now considers the consumer surplus of the aggregator as an active market participant. Constraint \((3.7b)\) enforces the supply and demand equilibrium, associated with the dual variable \(\lambda_t\),
representing the market clearing price, as seen by the aggregator in the cost function (3.5a). Finally, (3.7c)-(3.7e) ensure that, for each bid, the accepted volume lies between zero and the bid volume submitted to the market.

To take driving pattern uncertainty into account, constraints (3.5b)-(3.5e) in (3.5), can be replaced by their probabilistic counterparts, as described in § 2.3.4.

3.3.2 Bilevel model under market bid uncertainty

The bilevel problem comprising upper level problem (3.5) and a collection of lower level problems (3.7) determines how the aggregator should set the optimal bid prices $c_t^A$ taking into account the impact of these bids on the market clearing. To compute this impact, the aggregator needs to estimate the bid prices $(c_d^D, c_s^S)$ and volumes $(P_{dt}^{max}, P_{st}^{max})$ of other market participants, in order to recreate the market clearing problem (3.7). This information is however not available ex-ante. To take the uncertainty in market bids into account, the problem can be reformulated as a stochastic problem, where different scenarios $r$ for the bids placed in the market are considered, with probability of occurrence $\pi_r$.

\[
\begin{align*}
\min_{\Phi^{ULs}, \Phi^{LLs}} & \sum_r \pi_r \sum_t \lambda_{rt} P_{rt}^A \Delta t \\
\text{s.t.} & \quad E_{rt}^A = E_{r(t-1)}^A + P_{rt}^A \eta^A_t \Delta t + E_{t}^A,\text{arr} - E_{t}^A,\text{dep}, \forall t, \forall r, \quad (3.9a) \\
& \quad E_{t}^A,\text{min} \leq E_{rt}^A \leq E_{t}^A,\text{max}, \quad \forall t, \forall r, \quad (3.9b) \\
& \quad P_{t}^A,\text{min} \leq P_{rt}^A \leq P_{t}^A,\text{max}, \quad \forall t, \forall r, \quad (3.9c) \\
& \quad E_{t}^A(t=0) = E_{r(t=T)}^A, \quad \forall r, \quad (3.9d) \\
& \quad (3.11), \quad \forall t, \forall r, \quad (3.9e)
\end{align*}
\]

with decision variables for the upper level problem

\[\Phi^{ULs} = \{c_t^A, \forall t, \forall r; E_{t}^A(t=0)\}. \quad (3.10)\]

The market clearing price $\lambda_{rt}$ and the accepted volume of the aggregator’s bid $P_{rt}^A$, stem from the solution of the market clearing problem
for time step $t$ and scenario $r$,

$$
\text{Max. } \Phi_{Lls}^{\text{D}} \sum_d c_d \cdot P_d + c_r p_r - \sum_s c_s P_{s} \quad (3.11a)
$$

subject to

$$
\sum_d P_d + \sum_r p_r = \sum_s P_{s} : \lambda_r, \quad (3.11b)
$$

$$
0 \leq P_d \leq P_d^{\text{max}} ; \mu_r^{\text{min}}, \mu_r^{\text{max}}, \forall d, \quad (3.11c)
$$

$$
0 \leq P_{s} \leq P_{s}^{\text{max}} ; \mu_r^{\text{min}}, \mu_r^{\text{max}}, \forall s, \quad (3.11d)
$$

$$
0 \leq p_r \leq p_r^{\text{max}} ; \mu_r^{\text{min}}, \mu_r^{\text{max}}, \forall r, \quad (3.11e)
$$

with decision variables for the lower level problem

$$
\Phi_{Lls}^{\text{D}} = \{ \Phi_{r}^{\text{D}} ; \forall r, \forall t \}; \quad \Phi_{r}^{\text{Lls}} = \{ P_{s}^{\text{Lls}} ; \forall s; P_{d}^{\text{D}} ; \forall d; \forall r \}. \quad (3.12)
$$

The Lagrange multipliers of the constraints $\Phi_{dual} = \{ \Phi_{r}^{\text{dual}} ; \forall r, \forall t \}$ with

$$
\Phi_{r}^{\text{dual}} = \{ \lambda_{r} ; \{ \mu_{r}^{\text{min}} ; \mu_{r}^{\text{max}} \} \forall d; \{ \mu_{r}^{\text{min}} ; \mu_{r}^{\text{max}} \} \forall s; \mu_{r}^{\text{min}} , \mu_{r}^{\text{max}} \} \quad (3.13)
$$

are defined after the colon.

Note that, so far, the results of the different scenarios are not coupled. However, for the aggregator to formulate consistent bids, the bid curve should be nonincreasing (demand bid curve). To enforce that the bid price and accepted bid volume pairs satisfy this property, binary decision variables

$$
\Phi_{\text{cur}} = \{ \{ x_{r'} r' t ; y_{r'} r' t ; z_{r'} r' t \} ; \forall r, \forall r' > r, \forall t \} \quad (3.14)
$$

are introduced, and the following constraints are added to the problem

$$
\begin{align*}
\text{(3.15a)} & \quad c_r^A - c_r^A \leq x_{r' r'} t M^A, \quad \forall r, \forall r' > r, \forall t \smallskip \\
\text{(3.15b)} & \quad c_r^A - c_r^A \geq (x_{r' r'} t - 1) M^A, \quad \forall r, \forall r' > r, \forall t \\
\text{(3.15c)} & \quad P_r^A - P_r^A \leq y_{r' r'} t M^A, \quad \forall r, \forall r' > r, \forall t \\
\text{(3.15d)} & \quad P_r^A - P_r^A \geq (y_{r' r'} t - 1) M^A, \quad \forall r, \forall r' > r, \forall t \\
\text{(3.15e)} & \quad x_{r' r'} t + y_{r' r'} t = 2 z_{r' r'} t, \quad \forall r, \forall r' > r, \forall t
\end{align*}
$$

where $M^A$ and $M^A$ are large enough positive constants.

In the bid curve that is finally to be submitted to the market, the price-quantity pairs correspond to the bid prices and accepted bid volumes\(^3\) Note that the finally submitted bid volumes do not correspond to the maximum aggregated charging power as in (3.11c), this value is just used in the initial computation.
of the different scenarios. Fig. 3.3 shows an illustrative example of a bid curve. Note that one possible solution is to have different prices for the same volume (scenarios 2 and 3 in the figure). This can be interpreted as a given volume being optimal for a certain range of prices.

Figure 3.3: Exemplary demand bid curve using 6 scenarios.

### 3.3.3 MILP formulation

In order to obtain a solution for bilevel problem (3.9)-(3.15), the upper and lower level problems need to be jointly solved. The lower level problem (3.11) is a linear programming problem, and therefore convex. It can be replaced by its Karush-Kuhn-Tucker (KKT) conditions. This leads to the stationarity constraints,

\[
\begin{align*}
    c^S_{rst} - \lambda_{rt} - \mu^S_{rst} + \mu^S_{rst} &= 0, & \forall r, \forall s, \forall t, \\
    -c^D_{rdt} + \lambda_{rt} - \mu^D_{rdt} + \mu^D_{rdt} &= 0, & \forall r, \forall d, \forall t, \\
    -c^A_{rt} + \lambda_{rt} - \mu^A_{rt} + \mu^A_{rt} &= 0, & \forall r, \forall t,
\end{align*}
\]
3.3. Strategic centralized scheduling

and the complementarity slackness conditions,

\[ 0 \leq P^S_{rst} \perp \mu^S_{rst} \geq 0, \quad \forall r, \forall s, \forall t, \quad (3.17a) \]
\[ 0 \leq P^S_{rst} - P^S_{rst} \perp \mu^S_{rst} \geq 0, \quad \forall r, \forall s, \forall t, \quad (3.17b) \]
\[ 0 \leq P^D_{rdt} \perp \mu^D_{rdt} \geq 0, \quad \forall r, \forall d, \forall t, \quad (3.17c) \]
\[ 0 \leq P^D_{rdt} - P^D_{rdt} \perp \mu^D_{rdt} \geq 0, \quad \forall r, \forall d, \forall t, \quad (3.17d) \]
\[ 0 \leq P^A_{rt} \perp \mu^A_{rt} \geq 0, \quad \forall r, \forall t. \quad (3.17e) \]
\[ 0 \leq P^A_{rt} - P^A_{rt} \perp \mu^A_{rt} \geq 0, \quad \forall r, \forall t. \quad (3.17f) \]

The non-linearities associated with the complementarity slackness conditions (3.17) can be linearized with the introduction of integer variables, denoted \( \gamma \), and large enough constants, denoted \( M \), as described in [130]. Constraints (3.17a) and (3.17b) can be reformulated as

\[ P^S_{rst} \leq (1 - \gamma^S_{rst})M^P^{S,\min}, \quad \forall r, \forall s, \forall t, \quad (3.18a) \]
\[ \mu^S_{rst} \leq \gamma^S_{rst} M^{P^{S,\min}}, \quad \forall r, \forall s, \forall t, \quad (3.18b) \]
\[ P^S_{rst} - P^S_{rst} \leq (1 - \gamma^S_{rst})M^P^{S,\max}, \quad \forall r, \forall s, \forall t, \quad (3.18c) \]
\[ \mu^S_{rst} \leq \gamma^S_{rst} M^{P^{S,\max}}, \quad \forall r, \forall s, \forall t. \quad (3.18d) \]

Similarly, (3.17c) and (3.17d) can be reformulated as

\[ P^D_{rdt} \leq (1 - \gamma^D_{rdt})M^P^{D,\min}, \quad \forall r, \forall d, \forall t, \quad (3.19a) \]
\[ \mu^D_{rdt} \leq \gamma^D_{rdt} M^{P^{D,\min}}, \quad \forall r, \forall d, \forall t, \quad (3.19b) \]
\[ P^D_{rdt} - P^D_{rdt} \leq (1 - \gamma^D_{rdt})M^P^{D,\max}, \quad \forall r, \forall d, \forall t, \quad (3.19c) \]
\[ \mu^D_{rdt} \leq \gamma^D_{rdt} M^{P^{D,\max}}, \quad \forall r, \forall d, \forall t. \quad (3.19d) \]

Finally, (3.17e) and (3.17f) can be reformulated as

\[ P^A_{rt} \leq (1 - \gamma^A_{rt})M^P^{A,\min}, \quad \forall r, \forall t, \quad (3.20a) \]
\[ \mu^A_{rt} \leq \gamma^A_{rt} M^{P^{A,\min}}, \quad \forall r, \forall t, \quad (3.20b) \]
\[ P^A_{rt} - P^A_{rt} \leq (1 - \gamma^A_{rt})M^P^{A,\max}, \quad \forall r, \forall t, \quad (3.20c) \]
\[ \mu^A_{rt} \leq \gamma^A_{rt} M^{P^{A,\max}}, \quad \forall r, \forall t. \quad (3.20d) \]
These constraints introduce the additional auxiliary binary variables

\[ \Phi_{aux} = \left\{ \{ \gamma_{rst}^{S,min}, \gamma_{rst}^{S,max} \} \forall r; \{ \gamma_{rdt}^{D,min}, \gamma_{rdt}^{D,max} \} \forall d; \gamma_{rt}^{A,min}, \gamma_{rt}^{A,max} \} \forall r, \forall t \right\}. \tag{3.21} \]

The nonlinear cost term \( K_{rt} = \lambda_{rt} P_{rt}^A \Delta t \) in the objective function (3.9a) can be reformulated as an equivalent linear expression using the strong duality theorem. Applying the strong duality theorem to the lower level problems yields the equality

\[ \sum_d c_{rdt}^D P_{rdt}^D + c_{rt}^A P_{rt}^A - \sum_s c_{rst}^S P_{rst}^S = \mu_{rt}^{A,max} P_{rt}^{A,max} + \sum_s \mu_{st}^{S,\max} P_{st}^{S,\max} + \sum_d \mu_{dt}^{D,\max} P_{dt}^{D,\max}, \tag{3.22} \]

and further substituting \( c_{rt}^A \) using (3.16c) gives

\[ \sum_d c_{rdt}^D P_{rdt}^D + \lambda_{rt} P_{rt}^A - \mu_{rt}^{A,min} P_{rt}^{A,min} + \mu_{rt}^{A,max} P_{rt}^{A,max} - \sum_s c_{rst}^S P_{rst}^S = \mu_{rt}^{A,max} P_{rt}^{A,max} + \sum_s \mu_{st}^{S,\max} P_{st}^{S,\max} + \sum_d \mu_{dt}^{D,\max} P_{dt}^{D,\max}. \tag{3.23} \]

Because of complementarity, the terms \( \mu_{rt}^{A,min} P_{rt}^{A,min} \) and \( \mu_{rt}^{A,max} (P_{rt}^A - P_{rt}^{A,max}) \) can be eliminated, since they are equal to zero. With that, the term \( K_{rt} \) can be written as the linear expression

\[ \frac{K_{rt}}{\Delta t} = \sum_s c_{rst}^S P_{rst}^S - \sum_d c_{rdt}^D P_{rdt}^D + \sum_s \mu_{st}^{S,\max} P_{st}^{S,\max} + \sum_d \mu_{rdt}^{D,\max} P_{rdt}^{D,\max}. \tag{3.24} \]

In summary, the problem (3.9) (3.15) can be formulated as the following MILP problem.

\[
\begin{align*}
\text{Min.} \quad & \sum_r \pi_r \sum_t K_{rt} \tag{3.25a} \\
\text{s.t.} \quad & (3.9b)-(3.9c), (3.15), \tag{3.25b} \\
& (3.16), (3.18)-(3.20), \tag{3.25c} \\
& \Phi_{cur} \in \{0,1\}, \Phi_{aux} \in \{0,1\}. \tag{3.25d}
\end{align*}
\]
3.4 Social welfare maximizing decentralized scheduling of PEVs

The problem to be solved here is analogous to the problem in §3.2. The goal is to schedule the charging of PEVs in a way that maximizes social welfare, subject to the end-use constraints of the PEV drivers. However, instead of using the aggregated representation of the fleet (virtual batteries), each PEV is represented individually in this formulation, see §2.2. Moreover, the decisions on when to charge are made by the individual PEVs, not by the aggregator. The aggregator only plays a coordinating role in this scheme: It receives information from PEVs and broadcasts control signals back to them.

The problem described in §3.2 is applied in a day-ahead scheduling context. Therefore, because of the long lead time, the initial energy content of each virtual battery is considered an optimization variable, as discussed in §3.2. When scheduling individual vehicles, it makes sense to decide on the charging profiles closer to real time, since the individual behavior cannot be accurately predicted day-ahead. In contrast, the properties of a PEV aggregation can be predicted quite accurately, see §2.3.4. A receding time horizon is applied to the individual scheduling: The values of the optimization variables are computed for the given time horizon (e.g. 24 h), but only the actions related to the immediate time step are applied. At each new stage of the receding horizon, the representation of each PEV’s flexible demand is updated with new scenarios consistent with the current observations.
Chapter 3. Charging cost minimization

For the copper-plate market clearing this problem is formulated as

\[
\text{Max. } \Phi_{WD} \sum_{t=1}^{T} \left( \sum_d c_d^D P_{dt}^D - \sum_s c_s^S P_{st}^S \right) \quad (3.26a)
\]

s.t.

\[
\sum_d P_{dt}^D + P_t^A = \sum_s P_{st}^S, \quad \forall t, \quad (3.26b)
\]

\[
0 \leq P_{dt}^D \leq P_{dt}^{D,\text{max}}, \quad \forall t, \forall d, \quad (3.26c)
\]

\[
0 \leq P_{st}^S \leq P_{st}^{S,\text{max}}, \quad \forall t, \forall s, \quad (3.26d)
\]

\[
P_t^A = \sum_v P_{vt}^V, \quad \forall t, \quad (3.26e)
\]

\[
E_{vt}^V = E_{v(t-1)}^V + P_{vt}^V \eta_v^V \Delta t - E_{vt}^{V,\text{cons}}, \quad \forall v, \forall t, \quad (3.26f)
\]

\[
C_v^{V,\text{SOC}_{v,\text{min}}} \leq E_{vt}^V \leq C_v^{V,\text{SOC}_{v,\text{max}}}, \quad \forall v, \forall t, \quad (3.26g)
\]

\[
0 \leq P_{vt}^V \leq P_{vt}^{V,\text{max}}, \quad \forall v, \forall t, \quad (3.26h)
\]

\[
E_{v(t=0)}^V = E_{v(t=T)}^V, \quad \forall v, \quad (3.26i)
\]

where (3.26f)-(3.26i) correspond to (2.2)-(2.4)-(2.7), and with decision variables

\[
\Phi_{WD} = \{ P_{st}^S, \forall s, \forall t; P_{dt}^D, \forall d, \forall t; P_t^A, \forall t; P_{vt}^V, \forall v, \forall t \}. \quad (3.27)
\]

Since both the number of decision variables and constraints grow with the number of PEVs, solving this problem in a centralized way becomes intractable for a large fleet. For this reason, a decentralized approach based on the Alternating Direction Method of Multipliers (ADMM) is proposed [54]. A decentralized solution also has the advantage that the PEVs do not need to share private information with the aggregator. This approach is also very flexible: It can be applied to different possible optimization problems faced by the aggregator, as long as they are convex, see e.g. the tracking problem described later in §3.7. The setup can also be extended to include network constraints, as in [121], with an appropriate convexification of the power flow equations, or to consider individual PEV cost functions (e.g. battery degradation in a simplified form) in addition to the common cost function.
3.4. Social welfare maximizing decentralized scheduling

3.4.1 Optimal charging problem formulation

Consider a general charging optimization problem of the form

\[
\begin{align*}
\text{Min.} & \quad c(l, P^D, P^S) \\
\text{s.t.} & \quad l = \sum_v x_v, \\
& \quad Ax_v \leq b_v, \quad \forall v, \\
& \quad x_v^{\min} \leq x_v \leq x_v^{\max}, \quad \forall v.
\end{align*}
\]

(3.28a)  (3.28b)  (3.28c)  (3.28d)

The aggregated charging schedule of the fleet over time steps \( t \in \{1, \ldots, T\} \) is denoted \( l \in \mathbb{R}^T \), and is associated with the scalar cost \( c(l, P^D, P^S) \), which also depends on the accepted supply \( P^S = \{P_s^t, \forall s, \forall t\} \) and demand volumes \( P^D = \{P_d^t, \forall d, \forall t\} \). The objective function \( c(\cdot) \) is extended-valued, as in [121], with objective value \(+\infty\) meaning infeasibility (constraint violation). The charging power schedules of the individual vehicles are given by \( x \in \mathbb{R}^{T \times V} \), with \( x_v \in \mathbb{R}^T \) the column corresponding to vehicle \( v \in \{1, \ldots, V\} \).

Problem (3.26) is equivalent to problem (3.28) with the following definitions:

- \( \bar{l}_t := P^A_t \).
- \( \bar{x}_{vt} := P^V_{vt} \).
- The cost function \( c(\cdot) \) corresponds to minus the objective function (3.26a), and the indicator function of the constraints (3.26b)-(3.26d).
- Inequality (3.28c) enforces the energy constraints faced by each vehicle, i.e. constraints on the cumulative sum of the charging power over time. It is derived out of (3.26f), (3.26g) and (3.26i).
- Constraint (3.28d) enforces the power bounds, and corresponds to (3.26h).

Since driving patterns, i.e. arrival and departure times and trip energy consumption, are subject to uncertainty, a stochastic approach to this problem is more suitable. More precisely, \( b_v \) and the power bounds \( x_v^{\min} \) and \( x_v^{\max} \) can be random variables in practice.
It is assumed that it is possible to extract independent and identically distributed samples $k \in \mathcal{K} = \{1, \ldots, K\}$, each representing a different configuration of the fleet’s constraints. The problem \((3.28)\) can be reformulated as the stochastic problem

$$
\begin{align*}
\text{Min} \quad & \Phi_{WD} \left( \frac{1}{K} \sum_{k} c(l_k, P^D_k, P^S_k) \right) \\
\text{s.t.} \quad & l_k = \sum_{v} x_{kv}, \quad \forall k, \\
& Ax_{kv} \leq b_{kv}, \quad \forall v, \forall k, \\
& x_{kv}^{\text{min}} \leq x_{kv} \leq x_{kv}^{\text{max}}, \quad \forall v, \forall k,
\end{align*}
$$

with decision variables $\Phi_{WD} = \{x_k, \forall k; l_k, \forall k; P^D_k, \forall k; P^S_k, \forall k\}$. The subscript $k$ is used to refer to the particular realization of the random parameter, or particular decision made in scenario $k$. Although the cost function $c(\cdot)$ is considered deterministic here, in principle it is possible to define scenario-dependent cost functions, e.g. in the case of price uncertainty.

The problem is solved with a receding time horizon, such as in \([131, 132]\): The optimization is solved over a finite time horizon of $T$ steps, but only the action for the immediate time step $t = 1$ is actually implemented. At the subsequent time step, the random problem parameters ($b_{kv}, x_{kv}^{\text{min}}$ and $x_{kv}^{\text{max}}$) can be redefined according to the newly obtained information, i.e. new samples can be extracted that are consistent with the recent observations. The problem is then computed for the new time horizon, which shifts by one time step with respect to the previous horizon. The action taken by a vehicle at the immediate time step should be consistent across scenarios, which adds the constraint

$$x_{kv(t=1)} = x_{k'v(t=1)} \quad \forall v, \forall k, k' \in \mathcal{K}$$

(3.30)

to the problem. This problem can become intractable when a large number of scenarios and/or vehicles needs to be considered. Therefore, the problem is solved using ADMM. Thereby, the problem is decomposed into smaller subproblems, and the solution of the original problem is found iteratively.
3.4 Social welfare maximizing decentralized scheduling

3.4.2 Solving the optimal charging problem with ADMM

Problem reformulation

By introducing the auxiliary decision variables $\tilde{x}_k \in \mathbb{R}^{T \times V}$ and $\tilde{l}_k \in \mathbb{R}^T$, the optimization problem (3.29)-(3.30) can be formulated as the equivalent problem

$$\min_{\Phi_{WD}, \tilde{\Phi}_{WD}} \sum_k \frac{1}{K} c(l_k, P^D_k, P^S_k) + \sum_{kv} g_{kv}(x_{kv}) + f(\tilde{x}, \tilde{l})$$

subject to

$$x_k = \tilde{x}_k, \quad \forall k,$$

$$l_k = \tilde{l}_k, \quad \forall k.$$ 

The function $g_{kv}(x_{kv})$ is the indicator function on the set defined by the constraints (3.29c) and (3.29d), and $f(\tilde{x}, \tilde{l})$ is the indicator function on the set defined by the constraints (3.29b) and (3.30), now applied to the duplicated variables $\tilde{x} = (\tilde{x}_k, \forall k)$ and $\tilde{l} = (\tilde{l}_k, \forall k)$. This second function therefore contains all the constraint that link a) the scheduling decisions of one PEV to those of the other PEVs (3.29b), or b) the scheduling decisions of one PEV across its different driving pattern scenarios (3.30).

The problem above exhibits the two-part structure suitable for ADMM, with $\Phi_{WD}$ and $\tilde{\Phi}_{WD} = \{\tilde{x}_k, \forall k; \tilde{l}_k, \forall k\}$ the first and second block of variables, respectively. This problem can be divided into subproblems, that are solved by each agent (PEVs, aggregator) independently. This is because, as discussed above, the linking constraints have been shifted to the indicator function $f(\tilde{x}, \tilde{l})$. Through an iterative process, whereby the agents share information, the global solution can be found under conditions discussed later.

The augmented Lagrangian of this optimization problem is

$$L_{\rho}(\Phi_{WD}, \tilde{\Phi}_{WD}, u, w) = \sum_k \frac{1}{K} c(l_k, P^D_k, P^S_k) + \sum_{kv} g_{kv}(x_{kv}) + f(\tilde{x}, \tilde{l}) + \rho \frac{1}{2} \sum_{kv} \|x_{kv} - \tilde{x}_{kv} + u_{kv}\|^2_2$$

$$+ \rho \frac{1}{2} \sum_k \|l_k - \tilde{l}_k + w_k\|^2_2,$$

(3.32)
with the scaled dual variables \( w = (w_k, \forall k) \), and \( u = (u_k, \forall k) \), with \( u_k = (u_{kv}, \forall v) \). To obtain the unscaled dual variables, the scaled dual variables need to be multiplied with the penalty parameter \( \rho \).

### ADMM algorithm

The steps at each iteration of the ADMM algorithm are shown in Table 3.2. Here, the overline on variables \( x_v, u_v, i \) and \( d \) is used to denote the mean across samples, e.g. \( \overline{x}_v := 1/K \sum_k x_{kv} \). The iterations are indexed with \( m \).

#### Table 3.2: ADMM algorithm steps at each iteration.

<table>
<thead>
<tr>
<th>Step Description</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Φ(^{WD})-minimization step (for each agent/scenario in parallel):</strong></td>
<td>[ x_{kv}^{m+1} := \arg\min_{x_{kv}} \left( g_{kv}(x_{kv}) + \frac{\rho}{2} | x_{kv} - \tilde{x}<em>{kv}^{m} + u</em>{kv}^{m} |_2^2 \right) \forall v, \forall k ]</td>
</tr>
<tr>
<td><strong>Schedule aggregation (for each scenario in parallel):</strong></td>
<td>[ i_k^{m+1} := \left( \sum_v x_{kv}^{m+1} - l_k^{m+1} \right)/(V + 1) \forall k ]</td>
</tr>
<tr>
<td><strong>Φ(^{WD})-minimization step (for each agent/scenario in parallel):</strong></td>
<td>[ \tilde{x}<em>{kv(t=1)}^{m+1} := \overline{x}</em>{v(t=1)}^{m+1} + \overline{\tilde{x}}<em>{v(t=1)}^{m+1} - \overline{\tilde{l}}</em>{(t=1)}^{m+1} - \overline{d}_{(t=1)}^{m+1} \forall v, \forall k ]</td>
</tr>
<tr>
<td><strong>Dual variable update (for each agent/scenario in parallel):</strong></td>
<td>[ u_{kv}^{m+1} := u_{kv}^m + x_{kv}^{m+1} - \tilde{x}_{kv}^{m+1} \forall v, \forall k ]</td>
</tr>
<tr>
<td><strong>Dual variable aggregation:</strong></td>
<td>[ \overline{d}<em>{(t=1)}^{m+1} := 1/K \sum_k \left( \sum_v u</em>{kv(t=1)}^{m+1} - w_{kv(t=1)}^{m+1} \right)/(V + 1) ]</td>
</tr>
</tbody>
</table>

The \( Φ^{WD}\)-minimization step is carried out by all PEVs and the aggregator in parallel, which can also solve each scenario in parallel. Then, the charging schedules are communicated to the aggregator, which computes the imbalance \( i_k \) between the sum of individual charge profiles and the aggregated profile, normalized by the number of agents \((V + 1)\). The value of the imbalance is communicated to the vehicles. With this
information, the agents perform the $\tilde{\Phi}^{WD}$-minimization step in parallel, and, subsequently, the dual update in parallel. Note that for the $\tilde{\Phi}^{WD}$-minimization step, explicit solutions are available, so only simple algebraic operations need to be performed. Finally, the value of $\overline{d(t=1)}$ is calculated by the aggregator, based on the dual variables communicated by the vehicles. This value is used by the agents in the $\tilde{\Phi}^{WD}$-minimization step of the following iteration. The communication exchanged between the aggregator and the PEVs is depicted in Fig. 3.4. Note that the aggregator only needs to know the sum of schedules and dual variables, not the individual values.

![Diagram showing communication between aggregator and PEVs]

**Figure 3.4:** Communication exchanged between the aggregator and the PEVs. The PEVs communicate their charging schedules $x_{kv}$ and dual variables $u_{kv(t=1)}$ (for each scenario $k$) to the aggregator, while the aggregator broadcasts the imbalance values $i_k$ and the aggregated dual variable $\overline{d(t=1)}$. 
Chapter 3. Charging cost minimization

Convergence

For a detailed discussion on the convergence of ADMM see [133, §3.2]. Here, when the objective functions of the aggregator and vehicles are closed, proper, and convex, and a solution to the problem exists, there is convergence of the objective, residuals and dual variables. The stopping criterion is defined based on the norms of the primal $r^m$ and dual $s^m$ residuals,

$$\|r^{m+1}\|_2^2 = \sum_{kv} \|x_{kv}^{m+1} - \tilde{x}_{kv}^{m+1}\|_2^2 + \sum_k \|l_k^{m+1} - \tilde{l}_k^{m+1}\|_2^2,$$

$$\|s^{m+1}\|_2^2 = \sum_{kv} \|\tilde{x}_{kv}^{m+1} - \tilde{x}_{kv}^{m}\|_2^2 + \sum_k \|\tilde{l}_k^{m+1} - \tilde{l}_k^{m}\|_2^2.$$

The termination criterion proposed in [133, §3.3.1] is applied, imposing that the norms of the primal and dual residuals are small enough, i.e.

$$\|r^m\|_2 \leq \epsilon^\text{pri}, \quad \|s^m\|_2 \leq \epsilon^\text{dual},$$

where $\epsilon^\text{pri}$ and $\epsilon^\text{dual}$ are the feasibility tolerances for the primal and dual residuals, respectively. These tolerances are chosen based on absolute and relative tolerances, see details in [133, §3.3.1].

Communication availability

The proposed framework assumes PEVs communicate and participate in the iterative process even when they are not currently connected to the grid, since their actions throughout the simulated time horizon need to be taken into account. The PEVs can connect and disconnect several times throughout this horizon. In practice, it is more realistic to assume that vehicles are only able to participate in the iterative process while connected. However, their impact on demand in the future time steps needs to be taken into account. Otherwise, the optimality of the results can be seriously undermined. A possible solution is that PEVs communicate their constraints (according to different scenarios) to the aggregator before disconnecting. This would allow the aggregator to compute their virtual actions while they are disconnected. The only disadvantage, in this case, is that private information needs to be shared with the aggregator, which is otherwise not necessary when only control signals are exchanged.
3.4. Strategic decentralized scheduling

3.4.3 Driving pattern sampling

Driving pattern samples are obtained with the method explained in §2.1.2. When the simulation is initialized, a sample is chosen to represent the true realization throughout the whole simulation. At each stage of the receding time horizon, for each vehicle, the subset of samples from all generated samples that are compatible with observations are determined. Compatible samples are samples that satisfy the two following conditions:

1. They have the same current connection status transition as the reference sample (e.g. from connected to disconnected).

2. There exists a $x_{kv}$ for which $g_{kv}(x_{kv})$ is zero, given the battery energy content resulting from the previous stage of the receding horizon optimization.

From this subset of compatible samples, $K$ samples are randomly extracted. The extracted samples, may or may not contain the “true” realization sample.

3.5 Strategic decentralized scheduling of PEVs

In §3.4 PEVs are assumed to cooperate to find the charging schedules that maximize social welfare. In this section, PEVs behave strategically and only seek to minimize their individual charging costs. As in §3.4 the charging decisions are made close to real time and only for the immediate time step.

The approach described here is based on multi-agent systems and market-based control [55, 134]. In this type of framework, agents compete on a market for a resource, which they need as an input to their local control problem. In this decentralized approach, each PEV formulates its own bids, and the aggregator has simply the role of aggregating these bids. The aggregator therefore does not play an active role as in the centralized approaches, where it decides when to charge PEVs and when to purchase electricity for them. Compared with the approach in §3.4 the market-based control approach does not require an iterative
feedback process (one-shot auction). However, the intertemporal con-
strains of the vehicles are no longer handled explicitly, and this aspect
must therefore be integrated into the computation of the bids.

Thus, a crucial point of the market-based control approach is defining
an optimal bidding strategy for the agents. In theory, demand agents
such as PEVs would bid based on their willingness to pay for electricity
at a given time. It makes sense that their willingness to pay at a given
time depends on their urgency to charge, which again depends on state
information, such as the State of Charge (SOC), the time to departure
and the energy needed before departure. However, for flexible loads such
as PEVs, the willingness to pay at a given time should also depend on
price expectations. For example, if a vehicle expects several hours of
low prices while it is connected, it will not be willing to pay higher
prices at any time of that day. Therefore, PEVs need to make strategic
decisions, e.g. they need to decide whether to start charging at a given
time or wait for lower prices.

The main goal of the PEV agent is to minimize the costs of charging,
given the constraints imposed by its driving patterns and by physical
battery and charging infrastructure characteristics. It should therefore
set the bids in such a way that this goal is achieved. For this purpose,
an approach where PEVs learn their optimal charging strategy through
interaction with the market environment is adopted. To this end, the
reinforcement learning method known as Q-learning is applied, which
has often been used in the context of bidding in electricity markets, for
example in [135-139]. However, the existing literature shows examples
with only few agents (10 or less), while here a large number of agents
(PEVs) is considered. Note that PEVs compete with each other and
affect market prices with their decisions, if not individually, at least as a
group. To model the interaction between strategic agents explicitly with
mathematical programming techniques would require using Equilibrium
Problems with Equilibrium Constraints [140-142], which would not be
tractable when a large number of strategic agents needs to be considered.
Therefore, reinforcement learning offers an alternative approach that
can be applied in practice.
3.5. Strategic decentralized scheduling

3.5.1 General framework

In the market-based control approach, individual PEVs participate in the market by submitting demand bids. Through a Q-learning algorithm, vehicles learn how to setup their bids optimally over time. Each iteration of the Q-learning algorithm comprises a full day, with hourly time steps. At each time step, three stages are gone through:

1. Each PEV defines its demand bids for the next time step, based on its status, future energy requirements, and past experience (represented by the Q-values).

2. The PEV bids are aggregated and submitted to the market.

3. The market is cleared and the resulting price is communicated to the PEVs.

Note that, in this approach, bids are only computed for the next time step (e.g. next hour). This is because the PEVs need to update their energy status, and thus their urgency/willingness to pay, with each new time step. Therefore, this approach could be suitable for intra-day or real-time markets, but is not appropriate for day-ahead markets where decisions need to be taken for a longer time horizon.

3.5.2 PEV demand bids

PEV demand bids are defined as a function of physical battery constraints, charging urgency and a number of tunable parameters that are further explained below. The generic PEV bid used here consists of two blocks, as shown in Figure 3.5. The values $P_{vt}^{B,\text{min}}$ and $P_{vt}^{B,\text{max}}$ represent the minimum and maximum charging power at a given time step $t$. They are calculated taking into account both energy and power constraints, e.g. for the maximum power

$$P_{vt}^{B,\text{max}} = \min \left( \frac{C_v \text{SOC}_{vt}^{V,\text{max}} - E_v^{V(t-1)}}{\eta_v \Delta t}, P_{vt}^{V,\text{max}} \right), \quad (3.33)$$

where variable $C_v^V$ is the battery capacity of vehicle $v$, SOC$_{vt}^{V,\text{max}}$ the maximum allowed SOC, $E_v^{V(t-1)}$ the energy content at the end of the
previous time step, $\eta_v^V$ the charging efficiency, $\Delta t$ the duration of the time step, and $P_{vt}^{V,\text{max}}$ the maximum possible charging power.

The minimum charging power is calculated considering how much energy needs to be charged before departure vs. how much energy can be potentially charged in the following time steps until departure

$$ P_{vt}^{B,\text{min}} = \max \left( \min \left( \frac{E_{vt}^{V,\text{req}}}{\eta_v^V \Delta t} - P_{vt}^{V,\text{max}} (d_{vt}^V - 1), P_{vt}^{V,\text{max}} \right), 0 \right), $$

(3.34)

where parameter $d_{vt}^V$ denotes the time steps left until departure and $E_{vt}^{V,\text{req}}$ is the remaining energy to be charged before departure, defined as

$$ E_{vt}^{V,\text{req}} = \max \left( 0, E_{vt}^{V,\text{dep}} - E_{v(t-1)}^V \right), $$

(3.35)

where $E_{vt}^{V,\text{dep}}$ is the minimum energy that needs to be in the battery at the time of the next departure, which is computed with foresight\textsuperscript{4}. V2G is not considered here. Therefore, the value of $P_{vt}^{B,\text{min}}$ is zero or positive. Whenever $P_{vt}^{B,\text{min}}$ is larger than zero, this means that charging is partially inelastic, i.e. immediate charging is needed in order to be able to depart with a battery content no lower than $E_{vt}^{V,\text{dep}}$. Therefore, the price associated with the first bid block is set equal to the highest bid price allowed in the market, denoted $p_{vt}^{B,\text{max}}$, see Fig. 3.5. This bid block thus always makes sure that enough energy is charged, i.e.

\textsuperscript{4}In fact, this minimum energy corresponds to the lower energy trajectory $E_{vt}^{V,\text{low,free}}$ described in 2.3.2.
that end-use constraints are not violated. If the charging of the PEV is completely flexible, \( P_{vt}^{B,\text{min}} \) is equal to zero and the bid function has only one block. If charging is completely inelastic, then \( P_{vt}^{B,\text{min}} = P_{vt}^{B,\text{max}} \) and the function has a single block at the maximum price. If the vehicle is not connected at the given time step, then \( P_{vt}^{B,\text{max}} = 0 \) and the vehicle does not participate in the market. This is also the case for vehicles that have a full battery.

The bid price of the second block, denoted \( p_{vt}^{B} \), is defined as a function of the charging urgency and two tuning parameters \( b_v^B \) and \( c_v^B \),

\[
p_{vt}^{B} = \left[ b_v^B + c_v^B \left( \frac{E_{vt}^{V,\text{req}}}{d_v^V \eta_v^V P_{vt}^{V,\text{max}}} \right) \right]. \tag{3.36}
\]

The term in brackets represents the charging urgency, defined here as the fraction of the energy that needs to be charged until departure and the energy that could potentially be charged until departure \[94\]. If the vehicle has charged more than it is needed for the next trip, \( E_{vt}^{V,\text{req}} \) is zero, and therefore \( p_{vt}^{B} = b_v^B \). This means that the PEV might still want to charge further if prices are low enough, i.e. lower than or equal to \( b_v^B \). The rounding in (3.36), denoted by \( \lfloor \cdot \rceil \), is done to avoid too many different values of \( p_{vt}^{B} \) among the fleet, which would make the aggregation of bids cumbersome.

The objective of the learning algorithm is to find the combination of parameters \( b_v^B \) and \( c_v^B \) that minimizes the cost of charging, as explained in the next subsection. Those parameters, combined with the charging urgency, determine the price of the second bid block through equation (3.36). The bid volumes are however only dependent on the vehicle status and physical parameters. Parameter \( b_v^B \) can be interpreted as the price that a given vehicle considers low enough to start charging even if no energy is urgently needed. It is therefore the lower bound on a vehicle’s willingness to pay for charging. Parameter \( c_v^B \) determines the sensitivity to charging urgency of the willingness to pay for charging.

Although only two degrees of freedom, \( b_v^B \) and \( c_v^B \), are considered here, it would be possible to define more parameters to shape the bid blocks. However, there is a tradeoff between the number of parameters to be optimized, potentially yielding solutions closer to the optimum, and the convergence speed of the learning algorithm.
3.5.3 Learning algorithm

The machine learning algorithm adopted here is the reinforcement learning method known as Q-learning \[143\]. With this method, PEVs can discover their optimal bidding strategy through the experience obtained by interacting with the environment, which in this specific case is the electricity market. The so-called Q-values are the expected rewards of the possible state-action pairs, which are updated at each iteration of the algorithm. Due to the large number of agents to be modeled here, the Q-values are assumed to be independent of the state to reduce complexity. The state of the vehicle is however implicitly modeled in the bid function through the way the price $P^B_{vt}$ is defined in (3.36), based on charging urgency.

Therefore, the standard Q-value update equation \[143\] can be simplified 137 to

$$Q_{v}^{m+1}(a^m_v) = Q_{v}^{m}(a^m_v) + \alpha (R_{v}^{m+1} - Q_{v}^{m}(a^m_v)), \quad (3.37)$$

where $Q_{v}^{m}(a^m_v)$ is the Q-value associated with the action $a^m_v$, chosen out of the set of possible actions $A_v$ at iteration $m$, $R_{v}^{m+1}$ is the reward obtained by applying that action, and $\alpha$ is the learning rate, assumed constant. Each action $a^m_v \in A_v$ is defined by a pair $(b^B_v, c^B_v)$. Note that, unlike in §3.4, the iterations correspond to the actions taken at different days here, not to an iterative market clearing process at each time step.

The reward $R_v$ over a time horizon of length $T$ (e.g. one day) for a given vehicle at a given iteration is defined as

$$R_v = -\sum_{t=1}^{T} \lambda_t P^V_{vt} \Delta t - w \max(0, E^V_{v(t=0)} - E^V_{v(t=T)}). \quad (3.38)$$

The first term corresponds to the cost of purchasing electricity throughout horizon $t = \{1 \ldots T\}$, with the market clearing price $\lambda_t$ and the corresponding charging demand $P^V_{vt}$, which is determined according to the bid function. The second term is a penalty, weighted with a factor $w$, applied in the cases where the vehicle fails to buy enough energy to get back to the initial energy content. This is to discourage myopic behavior where part of the costs of charging would always be transferred to the time period beyond the optimization horizon. Note that, although new bids are computed at each time step, based on the updated urgency to charge, the parameters $b^B_v$ and $c^B_v$ remain the same throughout
3.5. Strategic decentralized scheduling

\( t = \{1 \ldots T\} \). Therefore, the reward of a given \((b_v^B, c_v^B)\) pair is computed for the full time horizon, as defined in (3.38).

To balance exploration vs. exploitation, an \(\epsilon\)-Greedy policy is applied to choose an action out of the possible set of actions \(A\). According to this policy, the agent will perform the action with the highest Q-value with probability \(1 - \epsilon\), and a random available action with probability \(\epsilon\). The chosen action remains the same for each of the time steps of the optimization horizon.

3.5.4 Bid aggregation

To ensure scalability, PEV bids are aggregated before they are submitted to the market. In the PowerMatcher framework \[90\], this aggregation is performed by the concentrator agent. The bid aggregation is done by horizontal summation of the individual demand curves. Let \(c_{at}^A\) denote a bid price within the unique set of bid prices from the individual PEV bids for time step \(t\), sorted in descending order \(a = \{1, \ldots, A\}\). The aggregated demand volume \(P_{at}^{A,\text{curve}}\) corresponding to the bid price \(c_{at}^A\) is computed as

\[
P_{at}^{A,\text{curve}} = \sum_v \left( P_{vt}^{B,\text{min}} + u_{vat} P_{vt}^{B,\text{max}} \right),
\]

where \(u_{vat} = 1\) if \(P_{vt}^{B} = c_{at}^A\), and \(u_{vat} = 0\) otherwise. The aggregated bid volumes \(P_{at}^{A,\text{max}}\) can then be computed out of the aggregated demand volumes as

\[
P_{at}^{A,\text{max}} = P_{at}^{A,\text{curve}} - P_{(a-1)t}^{A,\text{curve}}.
\]

A simple example of the bid aggregation process is shown in Fig. 3.6 for two PEVs.

In principle, it is possible to define a hierarchy of aggregation levels, e.g. aggregation at different network voltage levels. This is useful when network constraints are to be taken into account (e.g. one could set a cap on the total power consumed in an area). Here, results are presented for the Swiss spot market, where network constraints are not accounted for. Therefore, a single aggregation level is implemented.
Figure 3.6: Aggregation of individual bids by horizontal summation.
3.5. Strategic decentralized scheduling

3.5.5 Market clearing

The market clearing problem at time step $t$ is similar to problem (3.7)

$$\begin{align*}
\text{Max.} & \quad \sum_d c_d^D P_d^D + \sum_a c_a^A P_a^A - \sum_s c_s^S P_s^S \\
\text{s.t.} & \quad \sum_d P_d^D + \sum_a P_a^A = \sum_s P_s^S : \lambda_t, \\
& \quad 0 \leq P_d^D \leq P_{d,\text{max}}^D, \quad \forall d, \\
& \quad 0 \leq P_s^S \leq P_{s,\text{max}}^S, \quad \forall s, \\
& \quad 0 \leq P_a^A \leq P_{a,\text{max}}^A, \quad \forall a,
\end{align*}$$

(3.41a) (3.41b) (3.41c) (3.41d) (3.41e)

with decision variables

$$\Phi_{MC}^t = \{ P_s^S, \forall s; P_d^D, \forall d; P_a^A, \forall a \}. \quad (3.42)$$

The only difference compared with problem (3.7) is that the aggregator places several bid blocks, with $c_a^A$ the price of bid block $a$ and $P_{a,\text{max}}^A$ the corresponding bid volume. The bid prices and volumes of the different blocks stem from the aggregation of the individual PEV bids, as described in §3.5.4.

The resulting market price $\lambda_t$ is the Lagrange multiplier of the power balance equation (3.41b). After the market clearing, the vehicle can determine its subsequent consumption $P_{vt}^V$, based on the market clearing price and its bid function,

$$P_{vt}^V = \begin{cases} 
P_{vt,\text{min}}^B & \text{if } p_{vt}^B < \lambda_t < P_{vt,\text{max}}^B \\
(P_{vt}^B - P_{vt,\text{min}}^B)k_b & \text{if } p_{vt}^B = \lambda_t \\
P_{vt,\text{max}}^B & \text{if } p_{vt}^B > \lambda_t
\end{cases}$$

(3.43)

where $k_b \in [0, 1]$, when a bid block is only partially accepted ($k_b < 1$), denotes the fraction of the bid volume that is accepted. This value needs to be communicated to the PEVs together with the price.

With the charging power $P_{vt}^V$, the energy content of the battery is updated according to (2.1).
3.5.6 Driving pattern uncertainty

When driving patterns are considered deterministic, the same driving pattern sample (perfect forecast) is used in all iterations of the Q-learning algorithm. A more realistic approach is to assume that there is uncertainty in driving patterns. In this case, different samples of driving patterns are generated for each vehicle, and a random sample is selected at each new iteration.

3.5.7 Perfect market information benchmark

In the general case, PEVs are exposed to different market conditions (different sets of demand and supply bids for each hour) at every new day/iteration. By holding market conditions (the bids of market participants other than PEVs) constant, it is possible to establish a benchmark result representing “perfect market information”. The charging costs for a particular day are calculated by repeating that day many times until convergence of the Q-learning algorithm, and computing the costs at convergence. This approach has no practical relevance, but it can be used to gain some insight into the value of market information.

3.6 Price-based control

In this case, there is only unidirectional communication available. It is assumed that charging can only be steered through an exogenous TOU tariff, communicated to the vehicles in advance, e.g. day-ahead. This chapter describes how the optimal TOU tariff can be computed. The goal is, once more, to find the charging profile that maximizes social welfare, more precisely, to find the TOU tariff which induces a charging response that is welfare maximizing. This type of problem exhibits a bilevel structure: The upper level represents the welfare maximizing market clearing, whereas the lower level represents the aggregated optimal response to the TOU tariff\textsuperscript{5}, see Fig. 3.7. The market clearing in the upper level depends on the PEV charging demand determined in

\textsuperscript{5}Note that, in the optimal bidding problem in \textsection 3.3, the opposite is true: the lower level problem corresponds to the market clearing, and the upper level problem corresponds to the charging cost minimization.
the lower level, whereas the charging demand in the lower level depends on the TOU tariff determined in the upper level.

![Diagram of bilevel structure of the optimal TOU tariff problem.](image)

**Figure 3.7:** Bilevel structure of the optimal TOU tariff problem.

### 3.6.1 Defining a TOU tariff under perfect fleet information

In this case, to determine the response of PEVs to the optimal tariff the aggregated virtual battery representation is used. For smaller fleets, it could be possible to represent PEV responses in the lower level problem individually [115, 116], e.g. using the equations in §2.2. Alternatively, if an individual representation is computationally prohibitive, a more accurate representation of the PEV demand price response could still be obtained by clustering the fleet into several virtual batteries.
Chapter 3. Charging cost minimization

The upper level is formulated as follows,

\[
\begin{align*}
\max_{\Phi_{ULPC}, \Phi_{LLPC}} & \quad \sum_{t=1}^{T} \left( \sum_{d} c_{dt}^{D} P_{dt}^{D} - \sum_{s} c_{st}^{S} P_{st}^{S} \right) \\
\text{s.t.} & \quad \sum_{d} P_{dt}^{D} + P_{t}^{A} = \sum_{s} P_{st}^{S}, \ \forall t, \quad \text{(3.44b)} \\
& \quad 0 \leq P_{dt}^{D} \leq P_{dt}^{D,\text{max}}, \ \forall t, \forall d, \quad \text{(3.44c)} \\
& \quad 0 \leq P_{st}^{S} \leq P_{st}^{S,\text{max}}, \ \forall t, \forall s, \quad \text{(3.44d)} \\
& \quad \text{(3.46),} \\
\end{align*}
\]

with decision variables of the upper level problem

\[
\Phi_{ULPC} = \{ P_{st}^{S}, \forall s, \forall t; P_{dt}^{D}, \forall d, \forall t; \text{TOU}_t, \forall t \}. \quad \text{(3.45)}
\]

The aggregated charging profile \( P_{t}^{A} \) in \textbf{(3.44b)} stems from the solution of the lower level problem, where charging costs are minimized given the TOU tariff from the upper level,

\[
\begin{align*}
\min_{\Phi_{LLPC}} & \quad \sum_{t=1}^{T} \text{TOU}_t P_{t}^{A} \\
\text{s.t.} & \quad E_{t}^{A} = E_{(t-1)}^{A} + P_{t}^{A} \eta_{t}^{A} \Delta t + E_{t}^{A,\text{arr}} - E_{t}^{A,\text{dep}}, \ \forall t, \quad \text{(3.46b)} \\
& \quad E_{t}^{A,\text{min}} \leq E_{t}^{A} \leq E_{t}^{A,\text{max}}, \ \forall t, \quad \text{(3.46c)} \\
& \quad P_{t}^{A,\text{min}} \leq P_{t}^{A} \leq P_{t}^{A,\text{max}}, \ \forall t, \quad \text{(3.46d)} \\
& \quad E_{(t=0)}^{A} = E_{(t=T)}^{A}, \quad \text{(3.46e)}
\end{align*}
\]

with decision variables

\[
\Phi_{LLPC} = \{ P_{t}^{A}, \forall t; E_{(t=0)}^{A} \}. \quad \text{(3.47)}
\]

The problem with this formulation is that, in many cases, for a given TOU tariff, multiple charging profiles exist that solve the lower level problem, i.e. the lower level problem does not have a unique optimizer. In fact, the optimal solution of the bilevel problem would be to set a uniform tariff throughout the day (at any given price level), and then choose the charging profile that maximizes welfare. Since the tariff is flat, any charging profile leads to the same lower level costs, i.e. any
3.6. Price-based control

feasible charging profile is an optimizer of problem (3.46). However, there is no guarantee that PEVs would react in that particular way given the flat TOU tariff. Therefore, to avoid the problem of non-uniqueness of the solution of the lower level problem, the TOU tariff is forced to take discrete values that are different for each time step, i.e.

$$\text{TOU}_t \in \mathbb{Z}, \quad \forall t,$$  \hspace{1cm} (3.48)

$$|\text{TOU}_t - \text{TOU}_{t'}| \geq 1, \quad \forall t, \forall t' > t.$$  \hspace{1cm} (3.49)

Note that the optimal TOU tariff thus obtained from the optimization just “ranks” the welfare loss associated with generating the additional energy consumption at a given time step, with a higher TOU tariff at the time steps where increasing demand increases the welfare loss the most. The obtained TOU values have therefore an arbitrary magnitude. Hence, the TOU tariff obtained from the optimization needs to be further manipulated in order to obtain meaningful prices to be communicated to the fleet, see §3.6.3 below. Note that the TOU ranking does not necessarily correspond to the ranking of market clearing prices (as implicitly assumed in [115, 116]). The market clearing price only represents the marginal cost of an additional unit produced, but it does not characterize the welfare loss incurred when demand increases significantly. This is explained in Fig. 3.8. For an initial demand 1), the market clearing price is higher with supply curve b) than with supply curve a). However, if demand is increased to demand 2) (this would be the potential increase due to PEV charging), then the welfare loss is higher with supply curve a), since area A is larger than area C. If these supply curves correspond to two different time steps, this means that the TOU tariff at time step a) should be higher than that at time step b), although the price (without PEV demand) is lower at time step a) than at time step b).

To transform the bilevel problem into a MILP problem, as in §3.3 the lower level problem is replaced by its KKT conditions. Then, the complementarity slackness conditions are linearized by introducing integer variables, using the Fortuny-Amat McCarl linearization [130]. The detailed formulation of the MILP problem is given in Appendix A.
Figure 3.8: Impact of an increase in demand (from demand 1) to demand 2) on welfare, depending on the supply curve (supply a) or supply b)). Welfare loss a): A+B. Welfare loss b): B+C.
3.6. Price-based control

3.6.2 Defining a TOU tariff under partial fleet information

In practice, in this price-based scheme, it is unlikely that the aggregator has detailed information on the driving patterns of each PEV to be able to model the PEV price response accurately. The advantage of this type of scheme resides precisely in that the decisions are made locally by the PEVs, which in principle do not need to communicate their individual constraints to the aggregator. Thereby, drivers’ privacy is ensured, and only one-way communication is needed. To take the limitations on the availability of information into account, the problem (3.44)-(3.49) is adapted in order to base the PEV response to the TOU tariff on a coarser model. For this purpose, the equations of the lower level problem (3.46) are redefined. It is assumed that the aggregator only has an estimate of the total daily energy consumption of the PEV fleet, \( E^{A,\text{cons}} \), and of the total power that can be drawn by the fleet \( P^{A,\text{max}} \). These are realistic assumptions, since the aggregator needs to meter the consumption of the fleet for billing purposes, and it also knows how many vehicles it needs to manage, and potentially their nominal charging power. The lower level problem becomes

\[
\text{Min.} \quad \sum_{t=1}^{T} \text{TOU}_t P^A_t \quad \text{(3.50a)} \\
\text{s.t.} \quad \sum_t P^A_t \eta^A_t \Delta t = E^{A,\text{cons}}, \quad \text{(3.50b)} \\
0 \leq P^A_t \leq P^{A,\text{max}}, \quad \forall t. \quad \text{(3.50c)}
\]

This lower level problem replaces (3.46) in (3.44e). In this simplistic model, the evolution of the energy content over time (3.46b) is not tracked, since only the total energy consumption is known, see (3.50b). Moreover, the maximum power that can be drawn by the fleet is considered constant (3.46d) and not time dependent, as in (3.50c). However, if the aggregator could estimate the number of vehicles that are plugged-in at any point in time, a time-dependency could be established. This type of information could be obtained if the vehicles need to report when they plug in and out.
3.6.3 Constraints on the TOU tariff

In practice, additional constraints would need to be imposed on the TOU tariff, e.g. to ensure that the costs from purchasing the charging energy from the market can be recovered with a given margin $m^A$, i.e. $\sum_{t=1}^{T} \text{TOU}_t P_t^A = m^A + \sum_{t=1}^{T} \lambda_t P_t^A$. Instead of adding this type of constraints to the bilevel problem, which would increase its complexity, an appropriate TOU tariff can be derived ex-post from the TOU tariff obtained from solving the bilevel problem. Any TOU tariff obtained from a linear transformation of the optimal tariff $\text{TOU}_t^*$, $a + b\text{TOU}_t^*$ with $b > 0$, leads to the same response from the fleet. Minimizing over $\sum_{t=1}^{T} (a + b\text{TOU}_t^*) P_t^A$ is equivalent to minimizing over $\sum_{t=1}^{T} \text{TOU}_t^* P_t^A$ because the term $\sum_{t=1}^{T} P_t^A$ is constant through constraint (3.46e)/(3.50b). Therefore, the TOU tariff obtained from the optimization can be further manipulated to comply with other constraints, which therefore do not need to be included in the original optimization problem.

3.6.4 Possible extensions

Note that here a welfare maximizing approach to defining the optimal TOU tariff is adopted. However, it would be possible to extend the bidding strategy in §3.3 to consider an aggregator strategically defining the TOU tariff for the PEVs under its management. The aggregator would decide on the TOU tariff that minimizes the costs of procuring the resulting demand profile in the day-ahead market, while taking into account the impact of this demand on market prices. In this case, the upper level problem, i.e. the aggregator’s cost minimization problem, would be subject to two different problems: 1) the problem representing the PEVs response to the TOU tariff, and 2) the market clearing problem.
3.6. Hierarchical control

3.7 Hierarchical control - Combined centralized and decentralized framework

Hierarchical load control via aggregators \[144\] refers to the concept that load aggregators serve as intermediaries between the high-level power system and individual loads. In this context, the centralized and decentralized approaches are not necessarily mutually exclusive, but can be used complementarily at different stages. More specifically, the centralized approach in §3.3 can be used to derive the optimal aggregated charge profiles, and the cooperative decentralized approach in §3.4 can be used to distribute the aggregated profile among the individual PEVs. By combining the two strategies, it is possible to benefit from a) the fact that the aggregator can act strategically on markets, and b) the scalability, privacy and autonomy advantages of the individual decentralized scheduling.

The objective function of problem (3.28) can be redefined to ensure an optimal tracking of the aggregated profile derived from the optimization in §3.3. Let \( P^A^* \) denote the optimal aggregated demand profile according to the optimal bidding strategy in §3.3. Then, the objective function of (3.28) can be defined as the squared Euclidean norm of the deviations from the optimal aggregated charging profile \( c(l) = \| P^A^* - l \|_2^2 \) (or \( c(l) = \frac{1}{K} \sum_k \| P^A^* - l_k \|_2^2 \) in the stochastic version).

The use of ADMM for the problem described in §3.4 is not necessarily of practical interest, since it is unlikely that PEVs would be able to directly participate in the market through an iterative feedback process. This approach was mainly introduced to be able to assess the error due to representing PEVs in an aggregated way instead of individually. However, the use of ADMM to schedule individual vehicles in order to track an aggregated schedule is relevant in practice. Also, the convergence in the case of a quadratic cost function is much faster than in the case of a piece-wise linear cost function as in the problem in §3.4, since the former is strictly convex.

A further advantage of the combined centralized-decentralized approach is that local constraints (e.g. constraints on the loading of distribution grid transformers) could be taken into account in the decentralized problem, that are too detailed for the centralized aggregated problem. If considering these local constraints leads to significant deviations from the aggregated profile, these could be iteratively introduced into the
centralized problem \[91\].

The structure of the combined centralized-decentralized framework corresponds to a two-level hierarchical control strategy, with the centralized approach at the upper hierarchy level and the decentralized approach at the lower hierarchy level. Further, this structure could be extended to a multi-level strategy by introducing intermediate aggregation stages.

This combined approach is conceptually similar to the three-step approach proposed in \[94\]. In that framework, as a first step, individual PEV constraints are aggregated. In this thesis this is done by deriving the virtual battery model described in \[2.3.3\]. The second step in \[94\] is the fleet optimization, which determines the optimal aggregated schedule. Here, the optimal schedule is obtained from the optimal bidding strategy in \[3.2\]. The third step is the real-time control step, where individual vehicles are scheduled. In \[94\], market based control is proposed to derive the individual schedules. In this thesis both a market based control approach and another based on ADMM have been introduced. While the first has the advantage of being one-shot, but relies on heuristics, the second one is guaranteed to find the optimal solution, but requires iterative feedback process.

Because aggregated models do not perfectly represent individual requirements \[56\], small deviations from the aggregated schedule can be expected in the individual, real-time dispatch. The aggregator could, e.g., take positions in intra-day markets to cope with expected deviations from its day-ahead schedule.

### 3.8 Preliminary considerations on a simplified model

Before discussing the results of the described methods, some theoretical results are derived for a simplified charging optimization problem \[50\]. These theoretical results are important to understand the results of the more complex frameworks described above. The main goal is to characterize the general traits of the welfare maximizing and strategic solutions.

The following simplifying assumptions are introduced:
3.8. Preliminary considerations on a simplified model

- The fleet is considered homogenous, i.e. each vehicle has the same driving patterns and physical characteristics. In particular, each vehicle connects during the same time steps and consumes the same amount of energy.
- The charging power has no upper bound. The lower bound remains zero.
- The cost of serving load $P = (P_t, \forall t)$ is quadratic: $c(P) = aP + \frac{b}{2}P^\top P$.

The total (aggregated) energy required by the fleet is denoted $E_{A,cons}$.

3.8.1 Social welfare maximizing scheduling

Since all vehicles are identical and can therefore be assigned identical schedules, it is sufficient to consider the total (aggregated) charging power $l_t$. The centralized and decentralized approaches would be completely equivalent in this case. The goal is to minimize the quadratic system costs given a reference load profile $P_{ref}$ (load other than PEV load), i.e.

$$\text{Min. } \sum_t a(P_{ref}^t + l_t) + b/2(P_{ref}^t + l_t)^2$$

s.t. $\Delta t \sum_t l_t = E_{A,cons} : \lambda$, (3.51b)

$$l_t \geq 0 : \mu_t, \forall t.$$ (3.51c)

The Lagrangian of this problem is

$$L(l, \lambda, \mu) = \sum_t a(P_{ref}^t + l_t) + b/2(P_{ref}^t + l_t)^2$$

$$+ \lambda(E_{A,cons} - \Delta t \sum_t l_t) - \sum_t \mu_t l_t,$$ (3.52)

with $l = (l_t, \forall t)$ and the corresponding KKT conditions are

$$a + b(P_{ref}^t + l_t) - \Delta t \lambda - \mu_t = 0, \forall t,$$ (3.53)

$$0 \leq l_t \perp \mu_t \geq 0, \forall t,$$ (3.54)

$$\lambda(E_{A,cons} - \Delta t \sum_t l_t) = 0.$$ (3.55)
With that, the optimal aggregated charging power at time step $t$, $l_t^*$, can be written as

$$l_t^* = \max \left( 0, \frac{-a - bP_{t}^{\text{ref}} + \Delta t \lambda^*}{b} \right).$$

(3.56)

Introducing variable $k^* = \frac{-a + \Delta t \lambda^*}{b}$ yields

$$l_t^* = \max \left( 0, k^* - P_{t}^{\text{ref}} \right),$$

(3.57)

which can be interpreted as filling the valley of reference demand $P_{t}^{\text{ref}}$, where $k^*$ is the valley-filling level. A PEV demand “filling the valley” leads to a total demand curve that is as flat as possible. The value of $k^*$ is determined using $\Delta t \sum l_t^* = E^{A,\text{cons}}$.

The marginal cost (price) of electricity at time step $t$, $p_t$, corresponds to the first derivative of the cost function with respect to the total load $P_t$, i.e. $p_t = a + bP_t$, and is therefore a linear function of the total load. Thus, the welfare maximizing approach leads to a price curve that is as flat as possible.

The valley-filling result is shown for a stylized reference demand in Fig. 3.9. It is assumed that all vehicles are connected during a period of ten hours. The total PEV demand is scaled so that it represents 10% of the reference demand.
Figure 3.9: Reference load (without PEV load) and total load (including PEV load) for the welfare maximizing scheduling. The PEV load fills the valley of the reference load.
3.8.2 Strategic centralized scheduling

In the previous problem the total system costs are considered. Here, the goal is to minimize the costs for the fleet only, i.e. the costs of charging, given that prices correspond to \( p_t = a + b(P_{ref}^t + l_t) \),

\[
\begin{align*}
\text{Min.} & \quad (a + b(P_{ref}^t + l_t))^\top l \\
\text{s.t.} & \quad \Delta t \sum_t l_t = E_{A,cons}^t : \lambda, \\
& \quad l_t \geq 0 : \mu_t, \quad \forall t.
\end{align*}
\]

The Lagrangian of this problem is

\[
L(l, \lambda, \mu) = (a + b(P_{ref}^t + l_t))^\top l + \lambda(E_{A,cons}^t - \Delta t \sum_t l_t) - \sum_t \mu_t l_t,
\]

and the corresponding KKT conditions are

\[
\begin{align*}
a + b(P_{ref}^t + 2l_t) - \Delta t \lambda - \mu_t &= 0, \quad \forall t, \\
0 &\leq l_t \perp \mu_t \geq 0, \quad \forall t, \\
\lambda(E_{A,cons}^t - \Delta t \sum_t l_t) &= 0.
\end{align*}
\]

With that, the optimal aggregated charging at time step \( t \) can be written as

\[
l_t^* = \max \left( 0, -\frac{a - bP_{ref}^t + \Delta t \lambda^*}{2b} \right).
\]

Introducing variable \( k^* = \frac{-a + \Delta t \lambda^*}{2b} \) (the valley-filling level) yields

\[
l_t^* = \max \left( 0, k^* - \frac{P_{ref}^t}{2} \right),
\]

which can be interpreted as filling the valley of the reference demand \( P_{ref}^t \) divided by two. The value of \( k^* \) is determined using \( \Delta t \sum_t l_t^* = E_{A,cons}^t \).

This result is shown in Fig. 3.10. Compared with the welfare maximizing valley-filling results, see Fig. 3.11, during the time steps where the aggregator consumes more energy, the consumption is slightly reduced to lower the prices during those hours. On the other hand, during the
3.8. Preliminary considerations on a simplified model

time steps where the aggregator consumes less energy, the consumption
is slightly increased. Since the charging cost is computed out of the
product of PEV demand and prices, this cost can be reduced thereby,
compared with the welfare maximizing case. Fig. 3.10 also shows that
the resulting charging profile corresponds to a valley-filling result for
half the reference load.

Figure 3.10: Reference load (without PEV load) and total load (including
PEV load) for the centralized strategic scheduling. The PEV load fills the
valley of the reference load divided by two.
Figure 3.11: PEV load for the welfare maximizing (WM) and the strategic centralized (SC) scheduling.
3.8. Preliminary considerations on a simplified model

3.8.3 Strategic decentralized scheduling

In this case, each vehicle faces the following charging cost minimization problem,

\[
\begin{align*}
\text{Min.} & \quad (a + b(P^{\text{ref}} + \sum_{v'} x_{v'})^\top x_v \\
\text{s.t.} & \quad x_{vt} \geq 0 \quad : \mu_{vt}, \quad \forall t, \\
& \quad \Delta t \sum_t x_{vt} = E^{A,\text{cons}}/V : \lambda_v.
\end{align*}
\] (3.65a)

(3.65b)

(3.65c)

The Lagrangian of this problem is

\[
L(x_v, \lambda_v, \mu_v) = (a + b(P^{\text{ref}} + \sum_{v'} x_{v'})^\top x_v \\
+ \lambda_v \left( E^{A,\text{cons}}/V - \sum_t x_{vt} - \sum_t \mu_{vt} l_{vt} \right),
\] (3.66)

with \( \mu_v = (\mu_{vt}, \forall t) \) and the corresponding KKT conditions (for each vehicle \( v \))

\[
a + b(P^{\text{ref}} + \sum_{v'} x_{v't} + x_{vt}) - \Delta t \lambda_v - \mu_{vt}, \\
0 \leq x_{vt} \perp \mu_{vt} \geq 0, \quad \forall t, \\
\lambda_v (E^{A,\text{cons}}/V - \Delta t \sum_t x_{vt}) = 0.
\] (3.67)

(3.68)

(3.69)

At a Nash equilibrium, i.e. at an equilibrium where no PEV can reduce its costs by unilaterally changing its charging schedule, the KKT conditions for each of the vehicles need to be satisfied. Because the fleet is homogenous, each vehicle faces an analogous problem, i.e. the KKT constraints have the same form. A possible solution is for all the vehicles to have the same charging strategy, i.e. \( x_{vt} = l_t/V \). Hence, the index \( v \) in \( \lambda_v \) and \( \mu_{vt} \) can be dropped. The KKT conditions can be rewritten as

\[
a + b(P^{\text{ref}} + l_t + l_t/V) - \Delta t \lambda_t - \mu_t = 0, \\
0 \leq l_t \perp \mu_t \geq 0, \quad \forall t, \\
\lambda (E^{A,\text{cons}} - \Delta t \sum_t l_t) = 0.
\] (3.70)

(3.71)

(3.72)
This results in:

$$l_t^* = \max \left( 0, -a - bP_{ref}^t + \Delta t\lambda^* \right). \quad (3.73)$$

Introducing variable $k^* = -\frac{a + \Delta t\lambda^*}{V+1}b$ (the valley-filling level) yields

$$l_t^* = \max \left( 0, k^* - P_{ref}^t \frac{V}{V+1} \right), \quad (3.74)$$

which is interpreted as filling the valley of the reference demand $P_{ref}^t$ multiplied with $\frac{V}{V+1}$. The value of $k^*$ is determined using $\Delta t \sum_t l_t^* = E_{A,\text{cons}}$. For a fleet comprising a single vehicle $\frac{V}{V+1} = \frac{1}{2}$, and the solution of the aggregator’s centralized scheduling is recovered, i.e. the optimal solution if the vehicles act as a single entity. For an infinite population, i.e. $V \to \infty$, the welfare-maximizing solution is recovered. This means that when many strategic agents are competing against each other, their market power is lost. Therefore, the PEVs would be better off by letting an aggregator decide for them.

Fig. 3.12 shows the results for a fleet of $V = 5$ vehicles and a fleet of $V = 100$ vehicles. In both cases, the PEV demand has been scaled so that it corresponds to 10% of the reference demand. While for $V = 5$ the resulting total demand is still rather curved, for $V = 100$ the result corresponds almost to valley filling.
Figure 3.12: Reference load (without PEV load) and total load (including PEV load) for the decentralized strategic scheduling. The PEV load fills the valley of the reference load multiplied with $V/(V + 1)$.
3.9 Case study

In the following, a case study based on Swiss market and transportation data is presented, where the different methods described in this chapter are compared and analyzed.

3.9.1 Case study setup

Market data

To define the market’s supply and demand bids, aggregated bid curves of the Swiss spot market for electricity (day-ahead market), obtained from the European Energy Exchange (EEX), are used. In particular, a week in 2013 is simulated (21-27/10/13). Each day is divided into hourly time steps, i.e. $\Delta t$ corresponds to one hour. Fig. 3.13 shows the market prices and volumes for the simulated week and the previous week (14-20/10/13), without considering any additional PEV charging. In 2013, the volume traded in the day-ahead market corresponded approximately to 30% of the total energy consumed in Switzerland.
Figure 3.13: Market prices and volumes for the simulated week (21-27/10/13) and the previous week (14-20/10/13).
Market bid scenarios

As explained for the strategic bidding framework in §3.3.2, the aggregator does not know the market supply and demand bids ex-ante, and therefore needs to consider several market bid scenarios in the bidding problem. The scenarios for supply and demand bids are derived from past data. For the sake of simplicity, $R$ equally weighted scenarios are considered, i.e. $\pi_r = 1/R$, which are defined as the supply and demand bids of the $R$ weeks previous to the week under study. For example, for a given Monday at noon, the bids of the previous $R$ Mondays at noon are used as scenarios. This simple method to define scenarios is used here for demonstration purposes, but more advanced forecasting methods are possible. Note that, although there is a rich literature in price forecasting techniques, bid curve forecasting has received little attention.

Fleet characteristics and patterns

To see the effects of PEV charging more clearly, a relatively high PEV penetration of 10% is assumed, which would correspond to about 430,000 PEVs in Switzerland\textsuperscript{6}. The ensuing energy demand corresponds to about 7% of the energy traded in the day-ahead market. The sensitivity of some results to the PEV penetration is also analyzed. The driving patterns used in the case study, obtained from the tool MATSim (see §2.1.1), are specific to Switzerland and represent typical mobility behavior on weekdays. There is no equivalent model available for weekends, so the same mobility patterns are used for the weekends. In practice, weekend mobility patterns are very different to weekday patterns, since only the latter are strongly influenced by commuting patterns. Therefore, no quantitative analysis is possible for the weekend. Nevertheless, it is still possible to test and compare the performance of the described methods.

The transport simulation only provides data on trip distances. The corresponding energy consumption is derived from these with the factor 0.2 kWh/km\textsuperscript{146}.

\textsuperscript{6}The number of passenger cars in 2013 in Switzerland amounted to 4’320’885\textsuperscript{145}. 

\textsuperscript{146}
Fig. 3.14 shows the fraction of vehicles parked throughout the day, split by activity type. Two major dips in availability occur in the morning and evening, when many people drive their vehicles to work and then back home, and a smaller one occurs around noon. At any time, the percentage of vehicles parked is at least 60%\(^7\). Home is the most common parking location, followed by work and education, with 64.4% and 28.4% of the parking instances respectively. Other activities, such as shopping or leisure, generate only 7% of the total parking instances. This suggests that charging infrastructure would be most useful at home and at the workplace.

Fig. 3.15 displays the number of vehicles arriving and departing at each time step, normalized by the fleet size. The activity peaks occur in the morning and evening, as also suggested by Fig. 3.14.

![Figure 3.14: Fraction of vehicles parked by activity type.](image)

---

\(^7\)Note that only the vehicles parked during the full time step duration (one hour) are considered “parked” here, because it is assumed that vehicles with a short parking break will not connect to the network. The fraction of parked vehicles is higher if shorter time steps are considered. Typically, at least 90% of the vehicles are parked at any time.
Figure 3.15: Number of vehicles arriving and departing, normalized by the fleet size.
3.9. Case study

PEV parameters

The assumed maximum charging power for vehicles is 3.5 kW and the charging efficiency 90%. Each vehicle is assigned a battery with the capacity of 24 kWh, which is operated between 20% and 80% SOC. These parameters are reported in Table 3.3.

<table>
<thead>
<tr>
<th>$P_{\text{max}}^\text{V}$</th>
<th>$C_v^\text{V}$</th>
<th>$\eta_v^\text{V}$</th>
<th>$\text{SOC}_v^{\text{V,min}}$</th>
<th>$\text{SOC}_v^{\text{V,max}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.5 kW</td>
<td>24 kWh</td>
<td>90%</td>
<td>20%</td>
<td>80%</td>
</tr>
</tbody>
</table>

Driving pattern scenarios

To generate driving pattern samples, it is assumed that the order of performed activities (e.g., home-work-shop-home) given by the transport simulation is deterministic, but departure times, trip durations and trip energy are modeled as stochastic variables. Specifically, it is assumed that the trip departure time and trip duration are uniformly distributed ±30 minutes around their reference values, except when activities are within 60 minutes of each other. In such cases, in order to preserve the order of the activities, the support of the distribution is reduced. The trip consumption is also assumed to be uniformly distributed ±1 kWh around the reference value, which is obtained by multiplying the trip distance from the transport simulation with 0.2 kWh/km. The support of this distribution is reduced in the case of short trips where negative consumption values could be generated. With these distributions, different realizations of driving patterns are generated for each individual vehicle. These realizations are then used to obtain different samples of the aggregated variables, as explained in §2.3.4.

The chosen distributions are just exemplary distributions, in practice the aggregator would need to collect data from its PEV customers to find appropriate models for their stochastic behavior. However, the methods presented in this thesis remain valid for any distribution. In particular, the method used to reformulate the chance constraints (see §2.3.4) is not based on any particular distribution assumption.
Joint chance constraint in the centralized models

For the joint chance constraint described in §2.3.4 and used in the centralized approaches described in §3.2 and §3.3, the violation parameter $\epsilon$ is set to 0.1 and the confidence parameter $\beta$ to $10^{-7}$. Therefore, almost 1800 samples of driving patterns need to be extracted for each vehicle, see (2.34).

Fig. 3.16 shows the upper and lower energy bounds of the virtual battery, normalized by the usable fleet capacity\(^8\). The upper energy bound displays the same structure as the fraction of vehicles parked (compare with Fig. 3.14), with high values during the night and two dips in the morning and evening. The lower bound increases during the night until the early morning, representing the fact that vehicles need to charge their batteries before leaving in the morning. Fig. 3.16 shows, for each bound, the expected value and the extreme samples. Due to the large number of vehicles considered in the simulation, the extreme values are very close to the mean value in this case, see the discussion in §2.3.4.

Fig. 3.17 shows the upper and lower power bounds of the virtual battery, normalized by the total fleet charging capacity. As with the upper energy bound, the upper power bound displays the same structure as that of the fraction of parked vehicles. The lower bound is practically zero at all times, indicating that the amount of inflexible charging is negligible.

---

\(^8\)The usable capacity of each battery represents 60\% of the nominal battery capacity in this case, since it is assumed that the batteries are operated between 20\% and 80\% SOC, to limit battery degradation.
Figure 3.16: Upper and lower energy bounds ($E_{t,\text{max}}^A$ and $E_{t,\text{min}}^A$) of the virtual battery (obtained from 1800 samples). The energy content of the virtual battery is normalized by the total usable fleet capacity.
Figure 3.17: Upper and lower power bounds ($P_{t, \text{max}}^A$ and $P_{t, \text{min}}^A$) of the virtual battery (obtained from 1800 samples). The power values of the virtual battery are normalized by the sum of individual rated charging power values. The lower bounds are very close to zero and therefore not distinguishable from the x-axis.
3.9. Case study

ADMM parameters

Here, the parameters specific to the scheduling problem in §3.4 and the tracking problem in §3.7 are described. For the termination criterion proposed in [133, §3.3.1], the nominal absolute and relative tolerances are set to $10^{-4}$. The algorithm is stopped in any case after 4000/1000 iterations, in the scheduling problem and the tracking problem, respectively. The value of $\rho$ is set to 10 in the welfare maximizing optimization and to 5 in the tracking problem.

For each vehicle, 200 random samples of driving patterns are generated. At each stage of the receding horizon optimization $K = 5$ and $K = 10$ samples are taken into account in the welfare maximizing optimization and the tracking problem, respectively\(^9\). For more details on the sample selection procedure see §3.4.3.

Q-learning parameters

Here, the parameters specific to problem §3.5 are described. The value of $\epsilon$ in the $\epsilon$-Greedy algorithm is set to 0.1 and the learning rate $\alpha$ is set equal to 0.9. The training period for the Q-learning algorithm is from beginning of the simulated year until the simulated week.

Since price patterns depend strongly on the type of day being considered, three day types are defined in the Q-learning algorithm: weekdays, Saturdays and Sundays. For each type, a separate matrix of Q-values is stored and a different set of actions is defined. For weekdays, the set contains 60 different actions, combining 15 possible values of parameter $b$ with 4 possible values of parameter $c$. For Saturdays and Sundays, a set of actions with a lower cardinality is defined, since there are less of these day types: A set of 40 possible actions is defined for each of these day types ($10b \times 4c$). The same sets of actions are available to all vehicles. For each vehicle, 50 different samples of driving patterns are considered.

\(^9\)Note that in the ADMM algorithm, a much smaller number of driving pattern samples is considered than in the centralized problem. This is because it is probably not realistic to assume that the local controller at each PEV can solve a large amount of problems at a given time efficiently.
3.9.2 Additional benchmarks

Two additional charging scenarios are introduced as benchmarks, in order to complement the method comparison: uncontrolled charging, and a price control framework where the market prices are directly communicated to the vehicles.

Uncontrolled charging (dumb charging)

The assumption is that each PEV starts charging as soon as it is parked if charging is left uncontrolled. The resulting aggregated charging profile is displayed in Fig. 3.25d. The aggregator has to purchase this inflexible demand in the market, independently of the price. This is equivalent to a bid with the maximum allowed bid price and the aggregated charging demand at each time step as the bid volume. The comparison of this charging scenario with the other charging frameworks can be used to establish the value of charging flexibility.

Price-based control – direct pricing

In this case, it is assumed that the market prices, computed without consideration of the PEV demand, are directly used as TOU tariff. The PEVs decide on their optimal charging profile based on this tariff. However, to determine the actual prices and costs that would ensue, the market clearing is recomputed, considering the PEV demand this time.

3.9.3 Method comparison

First, the costs of purchasing energy resulting from the different charging approaches are compared, also taking into account the effect of market and driving pattern uncertainty. The costs per unit of energy purchased are reported in Table 3.4. These costs are computed by determining the total charging costs for the simulated week (given the aggregated scheduled charging power $P_{dt}^A$), and then dividing them by the total energy purchased during that week, i.e.

$$\frac{\sum_{d,t} P_{dt}^A \lambda_{dt}}{\sum_{d,t} P_{dt}^A},$$

(3.75)
where $d$ is the index for the days of the week, and $\lambda_{dt}$ denotes the market clearing price considering PEV demand.

Table 3.4: Cost comparison – cost of charging normalized by energy demand for the simulated week [€/MWh].

<table>
<thead>
<tr>
<th></th>
<th>perfect info</th>
<th>market uncertainty</th>
<th>driving info</th>
<th>market + driving uncertainty</th>
</tr>
</thead>
<tbody>
<tr>
<td>WM-C$^1$</td>
<td>24.44</td>
<td>-</td>
<td>24.72</td>
<td>-</td>
</tr>
<tr>
<td>ST-C$^2$</td>
<td>23.04</td>
<td>28.26</td>
<td>23.35</td>
<td>28.50</td>
</tr>
<tr>
<td>WM-D$^3$</td>
<td>23.77</td>
<td>-</td>
<td>23.98</td>
<td>-</td>
</tr>
<tr>
<td>ST-D$^4$</td>
<td>23.97</td>
<td>27.53</td>
<td>24.94</td>
<td>27.59</td>
</tr>
<tr>
<td>TOU-opt$^5$</td>
<td>30.08</td>
<td>-</td>
<td>30.21</td>
<td>-</td>
</tr>
<tr>
<td>TOU-dir$^6$</td>
<td>31.39</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>unc$^7$</td>
<td>42.98</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

$^1$ WM-C: welfare-maximizing centralized scheduling;
$^2$ ST-C: strategic centralized scheduling with one scenario and markup;
$^3$ WM-D: welfare-maximizing decentralized scheduling (without rolling horizon);
$^4$ ST-D: strategic decentralized scheduling;
$^5$ TOU-opt: TOU tariff based control - optimal tariff;
$^6$ TOU-dir: TOU tariff based control - direct pricing;
$^7$ unc: uncontrolled charging.

Note that, for the TOU tariff approaches, the true costs are reported, not the tariff-based costs: The charging response is calculated based on the TOU tariff, but the charging costs are computed based on the market prices that would ensue if this charging demand is included in the market clearing.

For the bidding strategy (strategic centralized approach), results are reported for a simulation considering a single market scenario. To make sure that the aggregator purchases the totality of the energy required, a maximum markup is added on the optimal bid prices determined with the bilevel optimization$^{10}$. Later, in §3.9.4 results are analyzed for

$^{10}$Due to the uncertainties related to the market bids and the corresponding clearing prices, using the bid prices from the bilevel optimization directly, when a single market scenario is considered, would many times mean that insufficient energy is purchased, even if the market prices are close to the estimated ones. If, at a given time step, the actual market price is only marginally lower than the expected price, the bid will not be accepted and therefore no energy will be purchased during that
several scenarios.

With this price markup in the strategic bidding, in all approaches except for the decentralized approaches, the same amount of energy is bought each day by design (demand is not shifted between days). For a fairer comparison, the rolling horizon discussed in \(3.4\) is not applied in the decentralized welfare maximizing approach here. Instead, the profiles defined at the beginning of the day for each day are considered, which is similar to the day-ahead perspective used in the centralized approaches. Thereby, it is made sure that the same amount of energy is purchased each day in the decentralized welfare maximizing scheduling. For the strategic decentralized approach, it is not possible to compute a day-ahead equivalent. It should be borne in mind when comparing the different approaches, that the demand in the strategic decentralized approach can be partially shifted between days, which gives this scenario a potential cost advantage.

The costs of the different approaches reported in Table 3.4 are discussed and compared in detail in the following.

**Comparison of the centralized approaches (WM-C/ST-C)**

If a strategic aggregator could perfectly forecast the bids of other market participants, it would slightly reduce the costs of charging compared with the welfare-maximizing strategy (in fact, compared with any strategy), both with perfect information and with driving pattern uncertainty, (6% improvement). The difference between the welfare-optimal costs and the strategic costs represents the market power potential of the aggregator, which is rather limited even for the relatively high PEV penetration of 10% assumed in the case study. Table 3.5 shows the sensitivity of this market power potential to the PEV penetration. The larger the PEV penetration, i.e. the larger the volume of energy purchased by the aggregator, the higher the difference between the welfare maximizing and the strategic approaches. This makes intuitive sense, since the larger the volume purchased by the aggregator, the more important its impact on prices.

The market prices and charge profiles of the two centralized approaches are shown in Fig. 3.18. The welfare-maximizing solution yields prices time step.
3.9. Case study

Table 3.5: Impact of PEV penetration on market power – cost of charging normalized by energy demand for the simulated week under perfect information [€/MWh].

<table>
<thead>
<tr>
<th>PEV penetration</th>
<th>2%</th>
<th>4%</th>
<th>6%</th>
<th>8%</th>
<th>10%</th>
</tr>
</thead>
<tbody>
<tr>
<td>WM-C(^1)</td>
<td>19.34</td>
<td>20.36</td>
<td>21.78</td>
<td>23.21</td>
<td>24.44</td>
</tr>
<tr>
<td>ST-C(^2)</td>
<td>19.27</td>
<td>20.01</td>
<td>21.01</td>
<td>22.01</td>
<td>23.04</td>
</tr>
<tr>
<td>WM-C – ST-C</td>
<td>0.07</td>
<td>0.35</td>
<td>0.77</td>
<td>1.21</td>
<td>1.40</td>
</tr>
</tbody>
</table>

\(^1\) WM-C: welfare-maximizing centralized scheduling;
\(^2\) ST-C: strategic centralized scheduling.

that are as flat as possible. Compared with this flat profile, if the aggregator sets bids strategically, it will aim to reduce prices slightly during the hours where charging is high, and increase the prices slightly during the hours where the charging is not as high. For this reason, the charge profile of the strategic bidding strategy has less pronounced peaks than the charge profile in the welfare-maximizing scheduling. These results are in accordance with the theoretical results derived in §3.8.

In the realistic case that the aggregator cannot perfectly forecast the other bids (market bid uncertainty), the aggregator would be better off not deciding on its own bidding strategy, but letting the market operator schedule the charging in a welfare-maximizing way (14% and 13% improvement with and without driving pattern uncertainty, respectively). The impact of market bid uncertainty on the strategic centralized approach can be seen in detail in Fig. 3.19. Although the general structure of the charge profiles is very similar, with and without market bid uncertainty, the differences in scheduling can lead to significant differences in the resulting prices, for example on the third day of the week in this case. In other cases, the differences are small, for example on the fourth and fifth day of the week. Table 3.6 shows that the higher the PEV penetration, the higher the additional costs due to market bid uncertainty. This is because the impact of the aggregator’s decisions on prices increases, and therefore the impact of non-optimal decisions, i.e. decisions based on imperfect market bid information, becomes more substantial.

Irrespective of the PEV penetration, the performance of the strategic bidding depends on how accurately the aggregator can forecast the market bids of other participants. The results of the strategic approach in
Figure 3.18: Comparison of the centralized approaches – Market prices and charge profiles for the simulated week (21-27/10/13). Driving patterns are assumed to be perfectly forecasted.

Table 3.4 are obtained using a single market bid scenario. These results can be improved by considering more scenarios, as discussed in §3.9.4.

The impact of driving pattern uncertainty on costs is only minor, around
### Table 3.6: Impact of PEV penetration on the cost increase due to market bid uncertainty – cost of charging normalized by energy demand for the simulated week [€/MWh].

<table>
<thead>
<tr>
<th>PEV penetration</th>
<th>2%</th>
<th>4%</th>
<th>6%</th>
<th>8%</th>
<th>10%</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ST-C</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>perfect info</td>
<td>19.27</td>
<td>20.01</td>
<td>21.01</td>
<td>22.01</td>
<td>23.04</td>
</tr>
<tr>
<td>market uncertainty</td>
<td>19.64</td>
<td>20.89</td>
<td>23.09</td>
<td>25.21</td>
<td>28.26</td>
</tr>
<tr>
<td><strong>ST-C</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>perfect info</td>
<td>-0.37</td>
<td>-0.88</td>
<td>-2.89</td>
<td>-3.20</td>
<td>-5.22</td>
</tr>
<tr>
<td>market uncertainty</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

1% ST-C: strategic centralized scheduling.

1%. This can be explained by the fact that the aggregated power and energy bounds can be quite accurately forecasted for a large fleet, see Fig. 3.16 and Fig. 3.17.
Figure 3.19: Impact of market bid uncertainty on the strategic centralized approach – Market prices and charge profiles for the simulated week (21-27/10/13). Driving patterns are assumed to be perfectly forecasted.
Comparison of the welfare maximizing approaches (WM-C/WM-D)

By comparing the centralized and decentralized approaches in the case of welfare maximization, it is possible to establish the impact on costs of the error induced by using an aggregated fleet representation: In the centralized approach, an aggregated model is used (virtual battery), whereas in the decentralized approach, each PEV is modeled individually. The problems are practically equivalent otherwise, under perfect information. Fig. 3.20 compares the price and charge profiles of the centralized and decentralized approaches in the welfare maximizing case, under perfect information. Both approaches try to generate price curves that are as flat as possible. However, the centralized model, because of the aggregation error, underestimates the available flexibility, generating a small peak in demand in the shoulder hours, which leads to a 3% increase in the costs of charging. In fact, the decentralized approach shows that it would be possible to charge during the nighttime only. On the last day (Sunday), the profiles are practically identical.
Figure 3.20: Comparison of the welfare maximizing approaches – Market prices and charge profiles for the simulated week (21-27/10/13). Driving patterns are assumed to be perfectly forecasted.
Comparison of the decentralized approaches (WM-D/ST-D)

In §3.8 it is shown that, in a simplified problem setup, the solution of the strategic approach comes close to that of the welfare maximizing approach when the number of strategic agents is very large. The two decentralized methods are compared in Fig. 3.21 for the case with perfect information. Because of the shortcomings of the heuristic Q-learning approach and the limited degrees of freedom provided by the structure of the bids and the available actions, the vehicles seem to only approximately establish the optimal price value at which to charge. This optimal value would correspond to the flat part of the price curve resulting from the welfare maximizing schedule. In some cases (e.g. days one, three, four), the vehicles start charging too soon, before the price is low enough. In other cases (e.g. day two), the vehicles do not charge enough during the valley hours, and therefore need to charge partly during the more expensive hours. The cost difference between the two decentralized approaches under perfect information is 1%.

In the realistic case where the PEVs need to learn their bidding strategy “on the fly” (market bid uncertainty), vehicles typically start charging too early, as soon as prices become reasonably low, see Fig. 3.22. This leads to 15% higher costs compared with the perfect information benchmark for the same scheme.

The impact of driving pattern uncertainty on the results of the welfare maximizing approach is negligible (less than 1% cost increase). In this cooperative approach, uncertainty in the individual driving patterns only marginally affects the aggregated behavior, i.e. the total PEV load is practically the same in all considered $K$ scenarios. Although individual loads may differ across the scenarios, at the aggregated level these deviations seem to compensate each other.

For the strategic approach, the impact of driving pattern uncertainty is quite important under perfect market information (4% cost increase). However, in the realistic case of market bid uncertainty, the difference between the costs with market bid uncertainty only and both market and driving pattern uncertainty is negligible. This means that, given market bid uncertainty, the additional impact of driving pattern uncertainty is unimportant.
Chapter 3. Charging cost minimization

Figure 3.21: Comparison of the decentralized approaches – Market prices and charge profiles for the simulated week (21-27/10/13). Driving patterns are assumed to be perfectly forecasted.
3.9. Case study

Figure 3.22: Impact of market bid uncertainty on the strategic decentralized approach – Market prices and charge profiles for the simulated week (21-27/10/13). Driving patterns are assumed to be perfectly forecasted.
Comparison of the strategic approaches (ST-C/ST-D)

In the realistic case of market and driving pattern uncertainty, results reported in Table 3.4 surprisingly show that the strategic decentralized approach performs slightly better than the strategic centralized approach. However, in the centralized approach a single market scenario is considered. Taking into account several market scenarios reduces the costs to 26.89€/MWh, as shown later in §3.9.4. Moreover, this result could be further improved by developing a more elaborate method to generate market scenarios. On the other hand, in the decentralized approach, market bid uncertainty is not explicitly handled, it is indirectly addressed by the learning algorithm. Therefore, if market outcomes become more volatile, it could be expected that the performance of the decentralized approach deteriorates more than that of the centralized approach. Moreover, the comparison is not completely fair, because in the decentralized approach shifting consumption between days is allowed, whereas this is excluded in the setup of the centralized approach here.

Comparison of the TOU tariff approaches (TOU-opt/TOU-dir)

Here, the charge profiles and the corresponding impact on prices of the two price control approaches are compared, see Fig. 3.23. The charge profiles are concentrated on few hours (those with the lowest TOU tariff), which induces higher peaks in prices compared with the approaches discussed so far, and therefore leads to higher costs. Directly using the market prices, computed without consideration of the PEV demand, as a tariff (TOU-dir), can generate even higher price peaks than using an artificial optimized tariff (TOU-opt), see discussion in §3.6.1. This leads to 4% higher costs for the direct TOU tariff compared with the optimized TOU tariff. Even if the optimal tariff is computed with limited information on the fleet (driving pattern uncertainty), the costs can still be reduced by almost 4% compared with the direct TOU tariff.
3.9. Case study

![Graphs showing market prices and charge profiles for TOU tariff approaches.](image)

(a) Market prices.
(b) Charge profiles.
(c) Market prices first day (Monday)
(d) Charge profile first day (Monday)

**Figure 3.23:** Comparison of the TOU tariff approaches – Market prices and charge profiles for the simulated week (21-27/10/13). Driving patterns are assumed to be perfectly forecasted.
Exogenous vs. endogenous price models (ST-C/TOU-dir)

In the strategic centralized scheduling approach described in §3.3, prices are endogenous parameters, since the market clearing is explicitly modeled through the bilevel structure of the problem. However, a common assumption in the literature is that PEV demand would not impact prices [27, 28, 31, 147], i.e. prices are assumed exogenous. If the aggregator would assume exogenous prices, then its demand bid volumes would correspond to the charging profile computed under direct pricing, since this is the optimum charging response given exogenous prices. As the comparison in Fig. 3.24 shows, the assumption of exogenous prices can be problematic, creating important price spikes, at least at the high PEV penetration assumed here (10%). Table 3.7 shows how the gap between the two approaches behaves at different PEV penetrations. At lower penetrations, because of the aggregation error, using the more complex model with endogenous prices actually leads to higher costs. However, when the PEV penetration increases, it becomes more and more important to use the model with endogenous prices. Accounting for the impact of PEV demand on prices is therefore crucial at high PEV penetrations.

Table 3.7: Impact of PEV penetration on the value of modeling prices endogenously – cost of charging normalized by energy demand for the simulated week under perfect information [€/MWh].

<table>
<thead>
<tr>
<th>PEV penetration</th>
<th>2%</th>
<th>4%</th>
<th>6%</th>
<th>8%</th>
<th>10%</th>
</tr>
</thead>
<tbody>
<tr>
<td>ST-C</td>
<td>19.27</td>
<td>20.01</td>
<td>21.01</td>
<td>22.01</td>
<td>23.04</td>
</tr>
<tr>
<td>TOU-dir</td>
<td>17.67</td>
<td>18.99</td>
<td>22.73</td>
<td>26.96</td>
<td>31.39</td>
</tr>
<tr>
<td>ST-C – TOU-dir</td>
<td></td>
<td>1.60</td>
<td>1.02</td>
<td>-1.72</td>
<td>-4.95</td>
</tr>
</tbody>
</table>

1 ST-C: **strategic centralized scheduling**;
2 TOU-dir: **TOU** tariff based control - **direct pricing**.
3.9. Case study

Figure 3.24: The value of modeling prices endogenously – Market prices and charge profiles for the simulated week (21-27/10/13) for the direct pricing approach (TOU-dir) and the strategic centralized approach (ST-C). Driving patterns and market prices/bids are assumed to be perfectly forecasted.
Chapter 3. Charging cost minimization

The value of charging flexibility

Finally, with uncontrolled (inflexible) charging, demand is more evenly distributed throughout the day (Fig. 3.25). Uncontrolled demand is higher between the morning and evening and shows peaks that coincide with the price peaks in the market. This explains the much higher costs associated with inflexible charging demand (between 37% and 87% higher). The charging demand peaks are related to commuting patterns: the first peak occurs when vehicles arrive at work and the second one when they arrive at home in the evening, see Fig. 3.15.

3.9.4 Considering several market scenarios in the centralized strategic approach

The results of the strategic centralized scheduling discussed so far are based on a single scenario and a large price markup, i.e. the bid price is set equal to the maximum bid price. In Table 3.8 the costs and purchased energy volumes using different numbers of scenarios are displayed.

The costs of the bidding strategy using a single scenario and no markup are the lowest, but in this case the aggregator does not manage to purchase all the required energy (10% shortfall), which is not a desirable situation. Although the costs are higher in the three-scenario case, the energy shortfall is only 3% in this case. The shortfall with one scenario and no markup is not especially large during this particular week, because the prices of the week previous to the simulated week are higher than those of the simulated week at almost all times, as seen in Fig. 3.13a. Therefore, since the computed bids are based on the past week’s bids, the bid prices defined by the aggregator are most of the times high enough. In general, considering only one scenario can lead to important energy shortfalls, and therefore it is expected that considering more market scenarios will, on average, reduce the costs of charging. This is shown in a more extensive study in [63].

Note that here the market scenarios are only based on the market bids of previous weeks. A further improvement would be achieved if a method to generate market bid scenarios was developed, which is out of the scope of this thesis.
3.9. Case study

![Graphs showing market prices and charge profiles.](image)

(a) Market prices.

(b) Charge profiles.

(c) Market prices first day (Monday)

(d) Charge profile first day (Monday)

**Figure 3.25:** Uncontrolled charging – Market prices and charge profiles for the simulated week (21-27/10/13). Driving patterns are assumed to be perfectly forecasted.
Table 3.8: Cost and energy comparison for different market bid scenario numbers.

<table>
<thead>
<tr>
<th></th>
<th>1 scen. with markup</th>
<th>1 scen.</th>
<th>2 scen.</th>
<th>3 scen.</th>
</tr>
</thead>
<tbody>
<tr>
<td>cost [€/MWh]</td>
<td>28.26</td>
<td>25.94</td>
<td>27.53</td>
<td>26.89</td>
</tr>
<tr>
<td>energy purchased [MWh]</td>
<td>3543</td>
<td>3171</td>
<td>3673</td>
<td>3537</td>
</tr>
<tr>
<td>energy shortfall [MWh]</td>
<td>0</td>
<td>371</td>
<td>61</td>
<td>89</td>
</tr>
<tr>
<td>energy overshoot [MWh]</td>
<td>0</td>
<td>0</td>
<td>191</td>
<td>83</td>
</tr>
</tbody>
</table>
3.9.5 Hierarchical control

Here the combined centralized-decentralized approach described in §3.7 is applied. Thereby, it is possible to establish the magnitude of the aggregation error in terms of the feasibility of the aggregated profile determined with the centralized approach. Fig. 3.26 shows the charging profile to be tracked, i.e. the aggregated schedule from the centralized strategic approach, and the charge profile resulting from scheduling individual PEVs using ADMM, with and without driving pattern uncertainty. In the case of driving pattern uncertainty $K = 10$ driving pattern scenarios are considered for each vehicle. The aggregation error seems to be small: the Euclidian norm of the tracking error, normalized by the total charging demand is 0.08% in the case of perfect information and 3.61% in the case of driving pattern uncertainty.

In summary, the aggregation error has two effects:

- An increase in the costs of charging because of the underestimation of the flexibility, see the comparison between the welfare maximizing approaches, and the comparison between exogenous and endogenous price models in §3.9.3.

- A mismatch between the desired aggregated schedule and the feasible total charging profile. This mismatch potentially leads to additional costs. To minimize these costs, the error in the different hours could be penalized with different weights, representing the costs of purchasing/selling the additional energy at a particular time-step, e.g. in the intra-day market.

Convergence results for the case with perfect information are shown in Fig. 3.27, displaying the optimality gap and the normalized residuals. The stopping criterion is met in this case at iteration 55, as represented by the dotted vertical line. The ADMM algorithm converges fast to a reasonably accurate solution, but afterwards the convergence rate is low. Since high accuracy is not necessary in this type of application, the number of required iterations for a good solution seems reasonable.
Figure 3.26: Tracking the aggregated schedule resulting from the centralized strategic approach with the decentralized ADMM-based approach.
Figure 3.27: Convergence of the decentralized ADMM-based approach, with perfect information. The stopping criterion is met at \( m = 55 \) iterations.
3.10 Concluding remarks

In this chapter, different approaches to the problem of scheduling PEV charging to reduce the cost of procuring the charging demand were discussed. These models can differ along the following dimensions: centralized/decentralized control, unidirectional/bidirectional communication, strategic/cooperative decision-making. Each combination of these characteristics presents different advantages and disadvantages, e.g. in terms of optimality, simplicity, privacy and scalability, see §3.1.5.

Based on the case study using data for Switzerland, the following conclusions are in order:

- A PEV aggregator can theoretically exercise market power, but in practice this requires a very good knowledge of the other market participants’ bids. In this context, it is crucial to develop appropriate models to estimate the supply and demand curves in the power market.

- For large fleets, driving pattern uncertainty has a negligible impact on the costs of charging for the centralized and/or cooperative approaches, since a) aggregated fleet characteristics can be quite accurately forecasted (centralized approaches), and b) the aggregated schedule is robust against differences in individual schedules across scenarios when the scheduling process is coordinated (welfare maximizing decentralized approach).

- Using reinforcement learning as a strategy for decentralized charging scheduling leads to results that are close to optimal. It remains to be explored how this performance would degrade with a higher volatility of market prices and/or driving patterns.

- Using TOU tariffs to shape PEV charging demand could be appropriate at low PEV penetrations, but, since this strategy leads to a high concentration of charging during certain hours, it is problematic at high PEV penetrations.

- The proposed virtual battery model seems to capture the available flexibility of the fleet accurately enough for large fleets, i.e. it only slightly underestimates the available flexibility and leads to an aggregated profile that can be sufficiently accurately tracked.
by individual PEVs. Results could be further improved by dividing the single aggregated representation into several aggregations of clusters of vehicles with similar characteristics and driving patterns.

- In any case, the gains from exploiting charging flexibility are substantial, compared with an uncontrolled charging scenario. Here, only the profits from exploiting flexibility were computed, but not the investment and operational costs in order to do so. These investment costs are mainly related to the necessary communication and control infrastructure, and are therefore expected to be low compared with the investment costs in electricity network infrastructure. The operational costs are basically the costs of the aggregator entity.
Chapter 4

Ancillary service provision
In this chapter, the framework introduced in §3 is extended to take into account that the aggregator can not only schedule the charging of the vehicles to minimize the costs of purchasing this energy, but can also use the charging, and even discharging, flexibility to provide ancillary services. These could be local ancillary services for Distribution System Operators (DSOs), such as voltage control [33, 34], and peak-shaving [35], or system-wide ancillary services for Transmission System Operators (TSOs), such as primary [36], secondary [27, 28, 37–39, 148] or tertiary frequency control [40]. Moreover, PEVs could help integrate intermittent Renewable Energy Sources (RES) [149].

Ancillary services are interesting because remuneration for these services is usually not only for the energy provided, but also for the reserved capacity [20]. Since vehicles are parked most of the time, but have batteries with a limited energy capacity, a double remuneration structure is particularly suitable. The ancillary services analyzed in this chapter are secondary frequency control, and RES real time balancing.

### Secondary frequency control

There are different definitions of frequency control ancillary services in different countries [150]. Here the focus is on the service that in most European countries is known as secondary frequency control, and in other countries is known as regulation, e.g. in the USA. These terms are used interchangeably here, and are interpreted according to the definition in [150]: “Secondary frequency control is a centralized automatic control that adjusts the active power production of the generating units to restore the frequency and the interchanges with other systems to their target values following an imbalance”. The associated control signal is usually known as Automatic Generation Control (AGC) signal or Load Frequency Control (LFC) signal.

Secondary frequency control is the second of three levels of frequency control. The first level is primary frequency control, which is “a local automatic control that adjusts the active power generation of the generating units and the consumption of controllable loads to restore quickly the balance between load and generation and counteract frequency variations” [150]. The third level is tertiary frequency control: “Tertiary frequency control refers to manual changes in the dispatching and commitment of generating units. This control is used to restore the primary
and secondary frequency control reserves, to manage congestions in the transmission network, and to bring the frequency and the interchanges back to their target value when the secondary control is unable to perform this last task \(^\text{[150]}\). Note that not all the three levels are present in all control areas.

There are differences among countries in the technical features of the regulation service, such as deployment start (ranging from a few tens of seconds to a few minutes), and the time to full availability (in the range of a few minutes) \(^\text{[150]}\). Apart from the differences in nomenclature and technical features, there are also differences in the economic features \(^\text{[151]}\). For example, reserves can be procured through a tendering process, though bilateral contracts, or in the spot market. When reserve capacities are procured through a tendering process or in a market, they can be paid at the submitted bid prices (pay-as-bid) or at a common clearing price (uniform pricing). In some cases, the reserve requests are proportional to the bidder’s contracted capacity (pro-rata activation), in other cases they are determined according to a separate bid for energy (merit-order activation). Moreover, in some cases symmetric capacities need to be offered (for up and down regulation), whereas, in other cases, it is possible to bid these components separately.

The framework here is kept as general as possible, but the two following assumptions are made:

- The energy payments can be neglected, i.e. they are assumed much smaller than the capacity payments, which is typically true, especially in Switzerland \(^\text{[29]}\), and partially in Germany \(^\text{[40]}\).

- The reserve requests are assumed to be proportional to the contracted capacity (pro-rata activation)\(^1\), as is the case in Switzerland. This plays a role in defining scenarios of reserve requests \(^\text{[4.4]}\).

\(^1\)For example, let us assume that the total required reserve capacity is 400 MW, and that a given participant offers 40MW, i.e. 10% of the total capacity. If, at a given time, 100MW up regulation is required in the system, then this participant needs to increase production or reduce consumption by 10MW.
RES real time balancing

By providing secondary frequency control, a PEV aggregator would contribute to balancing demand and supply of electricity in the system. A different option is to offer balancing services directly to the entities creating such imbalances, in the case that these are penalized. A balance group with an important share of intermittent RES power could be such an entity. In this case, the aggregator could enter a contract with the balance group to compensate the RES forecast error (or the balance group schedule in general) in real time.

Chapter structure

First, the relevant literature concerning PEVs offering regulation and RES balancing is reviewed in §4.1. Then, a centralized reserve scheduling scheme, extending the bidding strategy in §3.3, is introduced in §4.2. An alternative decentralized reserve scheduling scheme (based on the Alternating Direction Method of Multipliers (ADMM)), extending the framework in §3.4, is proposed in §4.3. The method used to generate ancillary service requests is explained in §4.4. Then, the results of the centralized and decentralized schemes are analyzed in §4.5. Finally, §4.6 concludes the chapter.

4.1 Literature survey and contributions

In the following, the literature on PEVs providing secondary frequency control and renewable energy balancing is surveyed, and the contributions of the models introduced later in this chapter are stated.

4.1.1 Secondary frequency control

Several publications have presented simulations of PEV aggregators managing vehicle charging in order to respond to an AGC signal from the TSO, focusing more on the deployment aspect of reserves and not on the reserve offering strategy [76, 152, 153]. In [152], an aggregation of plug-in hybrid electric vehicles, controllable loads and a combined-heat-and-power generation unit is managed with a Model Predictive
Controller that directly optimizes the setpoints of these units in response to a regulation signal. In [153], the AGC signal is distributed among vehicles according to individual participation factors, but the paper does not focus on how to define these factors, which is key given the uncertainty in the availability of vehicles. In [76], PEV charging stations are switched on or off, depending on the charging priority, to modify charging according to a regulation signal. This latter approach is unidirectional, meaning it requires no Vehicle to Grid (V2G) flows.

Other papers focus on determining how much regulation capacity to offer to the TSO. To address this question, it is important to consider the tradeoff between the costs of procuring charging demand and the revenues from providing regulation. More specifically, the shape of the charging profile, i.e. the charging setpoints derived from the positions taken by the aggregator in the spot market (or through other contracts), has an impact on the remaining flexibility that can be deployed for up and down regulation. The co-optimization of both charging costs and revenues from providing regulation has been addressed in [27, 28, 37–39]. Some of these papers look at the co-optimization problem from the perspective of individual PEVs [37–39]. In [37], an optimal charging control for individual PEVs providing regulation and charging, based on dynamic programming, is proposed. However, it is assumed that PEVs can only provide regulation while idle, i.e. they cannot offer regulation around their charging setpoint. In [38], the tradeoff between charging costs and revenues from regulation is balanced by defining an appropriate “preferred operating point” for each individual PEV, around which the charging rate is varied. The uncertainty related to the regulation requests is addressed in the co-optimization problem in [39], from the perspective of individual PEVs. As explained in [39], the decision to commit or not to provide a given regulation capacity for the subsequent time period is subject to a risk of either failing to provide the service or failing to meet the customers’ end-use requirements. However, from the point of view of an aggregator pooling a large number of resources, the uncertainty related to regulation capacity provision is significantly lower. Co-optimization problems from such an aggregated perspective are described in [27, 28], where bidding strategies for a PEV aggregator participating in energy and regulation markets are proposed. Note that, in all of the mentioned co-optimization papers, electricity prices are considered as an exogenous parameter, unaffected by PEV demand.

There are two major factors that affect the capability of a PEV aggre-
gation to provide regulation: a) the stochasticity and energy to power ratio of the regulation signal, and b) the uncertainty related to PEV driving patterns. The energy component of the regulation signal is crucial for the capability of energy-constrained resources such as PEVs to provide regulation [154]. Although the regulation signal exhibits some predictability one hour ahead [155], day-ahead forecasts are more difficult. However, some control areas might exhibit a deterministic component in their power imbalances, and therefore in their regulation signal [156]. It is in any case crucial to model the regulation requests and their associated uncertainty properly, in order to avoid violations of the regulation contract. This issue is only addressed in [39], and partially in [28], where a set of request scenarios are considered. The uncertainty in driving behavior has an impact on the availability of vehicles and on their energy requirements, and therefore reduces the reserve capacity potential of a PEV aggregation [157]. However, as the size of the aggregation grows, this aspect becomes less crucial. The uncertainty of driving patterns is only partially addressed in [28] by considering several scenarios of PEV charging constraints.

4.1.2 Renewable energy balancing

The synergies between plug-in electric vehicles and RES have been discussed e.g. in [149, 158]. On the one hand, RES can provide electricity for vehicle charging at low marginal costs and CO$_2$ emissions. On the other hand, PEVs could cover part of the increasing need for storage required to balance intermittent RES. Studies such as [149] and [159] conclude that PEVs can improve the ability to integrate wind power into power systems.

A number of papers have addressed the problem of how to balance wind with aggregations of PEVs [41–44]. These papers focus on the reserve deployment, but do not address how to define the charging baseline, i.e. there is no co-optimization of the goals of energy cost minimization and wind balancing revenue maximization. This type of co-optimization is found in [45, 46]. A three-level controller is proposed in [45]: 1) In the upper-level controller, the schedules of wind power plants and generators are optimized, 2) in the middle-level controller, the PEV demand is scheduled to achieve load following, and 3) in the lower-level controller, PEV charging is controlled in real time to regulate the grid frequency. In [46], a common bidding strategy for a PEV aggregator
and a wind energy producer is proposed, extending the work in [28]. Through the synergistic market participation of a wind producer and a PEV aggregator, it is possible to reduce the deviations from the day-ahead market setpoints caused by wind forecast errors.

The uncertainty in the availability of the fleet is not considered in [45]. In [46], the PEVs are modeled individually in the centralized optimization problem, which is not a tractable approach for large fleets. Moreover, none of the mentioned approaches provides (probabilistic) guarantees on the ability of the aggregator to fulfill its balancing contract given the uncertainty in driving patterns and balancing requests.

4.1.3 Contributions of the proposed charging and reserve scheduling models

In the following sections, a centralized and a decentralized approach to simultaneously schedule PEV charging and ancillary service reserves are introduced. The contributions of the proposed models are the following:

- In the centralized model, the impact of the aggregator’s bids on day-ahead market prices is taken into account, and the fleet’s capability to respond to uncertain regulation/balancing requests is modeled in a robust way.

- In the decentralized approach, the limitations of scheduling reserves individually in an uncoordinated way are overcome by letting PEVs cooperatively achieve a common objective by solving local optimization problems in parallel, while the aggregator serves as a coordinating agent.

- The impact of the availability of V2G, and of the characteristics of the regulation/balancing contract, on the ability of a PEV aggregator to offer regulation/balancing services is assessed.
4.2 Centralized reserve scheduling

In the following, a bidding strategy for a PEV aggregator placing demand bids in the day-ahead market, and selling capacity in the regulation market is described, extending the bidding strategy in §3.3. Both the options of providing regulation with and without the use of V2G are analyzed. Moreover, different settings of the regulation market are considered, to analyze their impact on the capacity that can be offered by PEV aggregations. In particular, some markets only allow symmetric bids for up and down regulation, and/or impose the requirement to offer the same regulation capacity for an extended period of time. These settings are different in different control areas/countries. For example, in Switzerland, the country used for the case study, symmetric capacities for a tender period of one week are required.

First, new virtual battery constraints, adapted to the problem of co-optimizing charging costs and reserve revenues, are described in §4.2.1. Then, a bidding strategy with regulation reserve provision is introduced in §4.2.2. This framework is adapted to the provision of renewable energy balancing reserves in §4.2.3. Finally, §4.4 describes how to generate scenarios of service requests.

4.2.1 Virtual battery constraints

The basic equations of the virtual battery model were described in §2.3. They consist of power and energy constraints, an equation describing the energy dynamics, and a constraint on the final energy content. To respond to ancillary service requests, the aggregator needs to deviate from the aggregated power and energy setpoints, $P^A_t$ and $E^A_t$ respectively, which are e.g. based on its commitments in the day-ahead market. For this reason, additional constraints need to be considered to make sure that the perturbed power and energy trajectories stay within predefined bounds. The absolute value of the normalized\(^2\) reserve energy requested at a given time step $t$ is denoted $e^+_t$ for up-reserves and $e^-_t$ for down-reserves, and is a random variable. Both $e^+_t$ and $e^-_t$ can be positive for a given time step $t$, since these variables represent the fraction of the time step that up/down-reserves are requested, respectively. For a

\[^2\text{The normalized requests lie between 0 and 1, where 1 represents the activation of all committed reserves.}\]
generator, providing down-reserves implies decreasing its power production. For an aggregation of PEVs, it implies increasing consumption. The opposite is true for up-reserve provision.

The aggregator can provide ancillary services with unidirectional charging only, i.e. by controlling the charging power of the vehicles, or by additionally using V2G, i.e. allowing discharging of energy from the PEV batteries to the grid. Although earlier studies on providing regulation typically assume V2G [37, 152], this feature is not necessary, since up regulation can not only be provided by discharging PEV batteries, but also by reducing charging with respect to a predefined setpoint [27, 28, 76], fixed e.g. in the day-ahead market. While only a limited amount of up regulation can be provided with unidirectional charging, V2G comes at a cost, due to the additional battery cycling and the corresponding battery degradation [20].

In the following, the additional power and energy constraints, adapting the virtual battery model to the problem of scheduling reserves, are described both for the unidirectional and V2G cases.

The power and energy bounds of the virtual battery (2.23)-(2.25) used in the previous chapter §3 are computed according to the following assumptions (see §2.3):

a) The energy content of the PEV batteries should reach the maximum State of Charge (SOC) at some point in time.

b) The energy content of the PEV batteries at the beginning and at the end of the horizon should be the same, i.e. the energy consumed should be recovered within the same day.

When regulation is to be provided, it is beneficial to operate the battery around a lower SOC, i.e. to drop assumption a). For this purpose, a shift from the reference that a maximum SOC is to be reached within the optimization horizon is introduced, denoted $\Delta E^A$. Moreover, assumption b) cannot be ensured any longer when the energy profile is perturbed by stochastic reserve requests. Therefore, an aggregated lower energy bound $E_{nt}^{A,\text{min,free}}$ is used, associated with the lower energy trajectories (denoted $E_{vt}^{V,\text{low,free}}$ and described in §2.3.2) that hold when assumptions a) and b) are dropped, i.e.

$$E_{nt}^{A,\text{min,free}} = \sum_v u_{vnt}E_{vt}^{V,\text{low,free}}, \quad \forall n, \forall t. \quad (4.1)$$
Fig. 4.1 illustrates the different bounds and the role of the energy shift. Without offering reserves (Fig. 4.1a), only the region between $E_{t}^{A,min}$ and $E_{t}^{A,max}$ is utilized. When reserves are to be provided (Fig. 4.1b), the batteries are operated around a lower SOC thanks to the shift $\Delta E$. The scheduled energy $E_{t}^{A}$ should still stay within the bounds $E_{t}^{A,min}$ and $E_{t}^{A,max}$, represented by the area shaded with the lighter grey color. When regulation requests are serviced, the energy profile will deviate from the scheduled one. These deviations should stay within the limits $E_{t}^{A,min,free}$ and $E_{t}^{A,max}$, represented by the area shaded with the darker grey color.

Therefore, constraints (2.23)-(2.25) still remain valid (unperturbed schedule). Additional constraints that must be satisfied by the perturbed energy and power profiles are described in the following.
4.2. Centralized reserve scheduling

Figure 4.1: Illustration of the role of the energy shift $\Delta E$ and of the different energy lower bounds.
Constraints to provide reserves with unidirectional charging

The following constraints are added to constraints \((2.23)-(2.25)\)^3

\[
P_t^A + C_t^- \leq P_t^{A,\text{max,free}} + \omega_t^{P_t^{A,\text{max,free}}}, \quad \forall t, \tag{4.2}
\]

\[
P_t^{A,\text{min,free}} + \omega_t^{P_t^{A,\text{min,free}}} \leq P_t^A - C_t^+, \quad \forall t, \tag{4.3}
\]

\[
E_t^A - \Delta E_t^A + \sum_{\tau=1}^{t} C_{\tau}^- e_{\tau}^- \eta_{\tau} A \Delta t - \sum_{\tau=1}^{t} C_{\tau}^+ e_{\tau}^+ \eta_{\tau} A \Delta t \leq E_t^{A,\text{max}} + \omega_t^{E_t^{A,\text{max}}}, \quad \forall t, \tag{4.4}
\]

\[
E_t^{A,\text{min,free}} + \omega_t^{E_t^{A,\text{min,free}}}
\]

\[
\leq E_t^A - \Delta E_t^A + \sum_{\tau=1}^{t} C_{\tau}^- e_{\tau}^- \eta_{\tau} A \Delta t - \sum_{\tau=1}^{t} C_{\tau}^+ e_{\tau}^+ \eta_{\tau} A \Delta t, \quad \forall t. \tag{4.5}
\]

Constraint \((4.2)\) ensures that the aggregator can provide the full contracted down-reserve capacity \(C_t^- \geq 0\) in addition to the scheduled charging power \(P_t^A\). Similarly, it should be able to reduce the scheduled charging power by the full contracted up-reserve capacity \(C_t^+ \geq 0\) without violating its power lower bound \((4.3)\). Since this lower bound is nonnegative (no V2G), this means that the scheduled charging power cannot be lower than the contracted up-reserve capacity. Note that in \((4.2)-(4.3)\) the upper and lower power bounds derived using the “free” lower energy trajectories are used, see \((2.10)-(2.11)\). Concerning the energy profile, it should stay within the energy bounds, coping with possible cumulative energy deviations due to providing reserves, see \((4.4)\) and \((4.5)\).

The random variables \(\omega_t^{P_t^{A,\text{max,free}}}, \omega_t^{P_t^{A,\text{min,free}}}\) and \(\omega_t^{E_t^{A,\text{min,free}}}\) represent the uncertainty in the aggregated virtual battery parameters \(P_t^{A,\text{max,free}}\), \(P_t^{A,\text{min,free}}\), and \(E_t^{A,\text{min,free}}\), respectively.

---

^3The index \(n\) has been dropped because only a single node is considered here.
4.2. Centralized reserve scheduling

Constraints to provide reserves with V2G

The following constraints are added to constraints (2.23)-(2.25):

\[
P_t^A + C^- \leq P_t^{A,\text{max},V2G} + \omega_t P_t^{A,\text{max},V2G}, \quad \forall t, \tag{4.6}
\]

\[
P_t^{A,\text{min},V2G} + \omega_t P_t^{A,\text{min},V2G} \leq P_t^A - C^+, \quad \forall t, \tag{4.7}
\]

\[
E_t^A - \Delta E^A + \sum_{\tau=1}^t C^-_\tau e^-_\tau \eta^A_\tau \Delta t - \sum_{\tau=1}^t C^+\tau e^+_\tau \eta^A_\tau \Delta t \leq E_t^{A,\text{max}} + \omega_t E_t^{A,\text{max}}, \quad \forall t, \tag{4.8}
\]

\[
E_t^{A,\text{min},\text{free}} + \omega_t E_t^{A,\text{min},\text{free}} \leq E_t^A - \Delta E^A + \sum_{\tau=1}^t C^-_\tau e^-_\tau \eta^A_\tau \Delta t - \sum_{\tau=1}^t C^+\tau e^+_\tau \Delta t / \eta^A_\tau, \quad \forall t. \tag{4.9}
\]

The constraints to provide regulation with V2G are similar to (4.2)-(4.5), but with slight modifications. First, the power bounds are replaced by new bounds when V2G is used, as explained in §2.3. Note that the lower bound \(P_t^{A,\text{min},V2G}\) now allows for negative power values. However, the power lower bound in constraint (2.25) remains unchanged, i.e. discharging is only allowed to provide regulation, not as a price-arbitrage strategy. Thereby battery degradation is limited. Concerning the energy profile, it should stay within the energy bounds, coping with possible cumulative energy deviations due to providing reserves, see (4.8)-(4.9). Since the up-reserve requests could be (but not necessarily are) provided by discharging batteries, the discharging efficiency is used in (4.9), instead of the charging efficiency as in (4.5). If inequality (4.9) holds using the discharging efficiency for up-reserves, then it also holds using the charging efficiency. Also, if inequality (4.8) holds using the charging efficiency for up-reserves, then it also holds using the discharging efficiency.

\[\text{The index } n \text{ has been dropped because only a single node is considered here.}\]
Sources of uncertainty

The constraints above are affected by two sources of uncertainty: the uncertainty in driving patterns, represented by the \( \omega \)-variables, which is discussed in §2.3.4, and the uncertainty related to the reserve requests, represented by the \( e \)-variables. The joint chance constraint introduced in (2.29) now includes the basic constraints (2.23)-(2.25), and also

- (4.2)-(4.5) in the unidirectional case, and
- (4.6)-(4.9) in the V2G case.

To reformulate the joint chance constraint, the approach proposed in [101] and described in §2.3.4 is also applied: A robust optimization problem with bounded uncertainty is solved, where the uncertainty bounds are obtained from a random scenario-based program. The bounded uncertainty set is defined by a hyper-rectangle. In contrast to the joint chance constraint in §2.3.4, in this case there is a product between optimization variables and random variables. In particular, the optimization variables representing the reserved capacity, \( C^-_\tau \) and \( C^+\tau \), multiply the random parameters \( e^-\tau \) and \( e^+\tau \), respectively, which means that the simplification from (2.32) to (2.33) is no longer possible.

Defining \( x \in \mathbb{R}^{T+1}_+ \) as \( x = (E^A_{t=0}; P^A_t, \forall t) \), and \( y \in \mathbb{R}^{2T}_+ \) as \( y = (C^+_t, \forall t; C^-_t, \forall t) \) the joint chance constraint can be described generically as

\[
P(\omega \in \Omega, e \in E \mid \max_{j=1,\ldots,J} a_j^T x + c_j(e)^T y + \omega_j - b_j \leq 0) \geq 1 - \epsilon, \quad (4.10)
\]

where \( \omega \in \Omega \) is the vector of uncertainties related to the \( \omega \)-variables and \( e \in E \) is the vector of uncertainties related to the \( e \)-variables. The function \( c_j(e) : \mathbb{R}^{2T} \rightarrow \mathbb{R}^{2T} \) is linear.

Because the constraints included in the joint chance constraint are linear with respect to the uncertainty, one way to approach the problem is to enumerate all the vertices of the hyper-rectangle \( B^* \) in which the uncertainty is confined [101], and enforce the original constraints at all the vertices. This would result in \( J2^{n_{hr}} \) constraints, where \( J \) is the number of constraints affected by the uncertainty \( (J = 8T) \) and \( n_{hr} \) is the dimension of the hyper-rectangle. The dimension of the hyper-rectangle and the number of samples \( K \) to be drawn to define its bounds will be
specified in the following. Because of the structure of the constraints, and the fact that $y$ is nonnegative, it is possible to determine a-priori at which vertex each constraint can be potentially binding. Therefore, it is enough to enforce each of the $J$ constraints at a particular vertex, as explained in the following. As a consequence, applying the robust approach does not have an impact on the number of constraints of the problem, it just affects their specific parameters.

**Reformulation of joint chance constraint**

Considering a set of scenarios $k = \{1, \ldots, K\}$ of the uncertain variables, constraints (4.2)-(4.5) can be reformulated as

\[
P_t^A + C^-_t \leq P_t^{A,\text{max,free}} + \min_k (\omega_{kt}^{P_t^{A,\text{max,free}}}), \quad \forall t, \tag{4.11}
\]

\[
P_t^{A,\text{min,free}} + \max_k (\omega_{kt}^{P_t^{A,\text{min,free}}}) \leq P_t^A - C^+_t, \quad \forall t, \tag{4.12}
\]

\[
\sum_{\tau=1}^t (P_{t}^A \eta_{t}^A \Delta t + E_{t}^A,\text{arr} - E_{t}^A,\text{dep}) - \Delta E^A
\]

\[
+ \sum_{\tau=1}^t C^-_\tau \max_k (e^-_{k\tau}) \eta_{t}^A \Delta t - \sum_{\tau=1}^t C^+_\tau \min_k (e^+_{k\tau}) \eta_{t}^A \Delta t \leq E_{t}^{A,\text{max}} + \min_k \left( \omega_{kt}^{E_{t}^{A,\text{max}}} + \sum_{\tau=1}^t \left( \omega_{kt}^{E_{t}^{A,\text{dep}}} - \omega_{kt}^{E_{t}^{A,\text{arr}}} \right) \right), \quad \forall t, \tag{4.13}
\]

\[
E_{t}^{A,\text{min,free}} + \max_k \left( \omega_{kt}^{E_{t}^{A,\text{min,free}}} + \sum_{\tau=1}^t \left( \omega_{kt}^{E_{t}^{A,\text{dep}}} - \omega_{kt}^{E_{t}^{A,\text{arr}}} \right) \right)
\]

\[
\leq \sum_{\tau=1}^t (P_{t}^A \eta_{t}^A \Delta t + E_{t}^A,\text{arr} - E_{t}^A,\text{dep}) - \Delta E^A
\]

\[
+ \sum_{\tau=1}^t C^-_\tau \min_k (e^-_{k\tau}) \eta_{t}^A \Delta t - \sum_{\tau=1}^t C^+_\tau \max_k (e^+_{k\tau}) \eta_{t}^A \Delta t, \quad \forall t. \tag{4.14}
\]

From these constraints and (2.23)-(2.25), it is clear that the uncertain inputs whose upper and lower bounds define the hyper-rectangle are the following:
• Variables related to driving pattern uncertainty
  
  – Lower bound of $\omega_t^{P_{A,\text{max}}}$ for all $t$.
  
  – Upper bound of $\omega_t^{P_{A,\text{min}}}$ for all $t$.
  
  – Lower bound of $\omega_t^{E_{A,\text{min}}}$ + $\sum_{\tau=1}^{t} (\omega_{\tau}^{E_{A,\text{dep}}} - \omega_{\tau}^{E_{A,\text{arr}}})$ for all $t$.
  
  – Upper bound of $\omega_t^{E_{A,\text{max}}}$ + $\sum_{\tau=1}^{t} (\omega_{\tau}^{E_{A,\text{dep}}} - \omega_{\tau}^{E_{A,\text{arr}}})$ for all $t$.
  
  – Lower bound of $\omega_t^{P_{A,\text{max},\text{free}}}$ for all $t$.
  
  – Upper bound of $\omega_t^{P_{A,\text{min},\text{free}}}$ for all $t$.
  
  – Lower bound of $\omega_t^{E_{A,\text{min},\text{free}}}$ + $\sum_{\tau=1}^{t} (\omega_{\tau}^{E_{A,\text{dep}}} - \omega_{\tau}^{E_{A,\text{arr}}})$ for all $t$.

• Variables related to regulation request uncertainty
  
  – Upper and lower bound of $e_t^+$ for all $t$.
  
  – Upper and lower bound of $e_t^-$ for all $t$.

Therefore, the dimension of the hyper-rectangle is $n_{hr} = 9T$ and the number of bounds to be computed is $11T$ (or $4T$ without driving pattern uncertainty), which imposes the condition

$$K \geq \left[ \frac{1}{\epsilon} \frac{e}{e - 1} \left( 11T - 1 + \ln \frac{1}{\beta} \right) \right]$$

(4.15)

on the number of samples that needs to be extracted.

For the V2G case, the constraints can be reformulated analogously:

$$P_{t}^{A,\text{min}} + \max_k (\omega_{kt}^{A,\text{min}}) \leq P_{t}^{A} \leq P_{t}^{A,\text{max}} + \min_k (\omega_{kt}^{A,\text{max}}), \quad \forall t,$$

(4.16)

$$E_{t}^{A,\text{min}} + \max_k \left( \omega_{kt}^{A,\text{min,free}} + \sum_{\tau=1}^{t} (\omega_{\tau}^{E_{A,\text{dep}}} - \omega_{\tau}^{E_{A,\text{arr}}}) \right)$$

$$\leq \sum_{\tau=1}^{t} (P_{\tau}^{A} \eta_{\tau}^{A} \Delta t + E_{\tau}^{A,\text{arr}} - E_{\tau}^{A,\text{dep}})$$

$$\leq E_{t}^{A,\text{max}} + \min_k \left( \omega_{kt}^{A,\text{min,free}} + \sum_{\tau=1}^{t} (\omega_{\tau}^{E_{A,\text{dep}}} - \omega_{\tau}^{E_{A,\text{arr}}}) \right), \quad \forall t,$$

(4.17)
4.2. Centralized reserve scheduling

\[ P_t^A + C_t^- \leq P_t^{A,\text{max,V2G}} + \min_k (\omega_{kt}^{A,\text{max,V2G}}), \quad \forall t, \]  
(4.18)

\[ P_t^{A,\text{min,free}} + \max_k (\omega_{kt}^{A,\text{min,free}}) \leq P_t^{A,+}, \quad \forall t, \]  
(4.19)

\[
\sum_{\tau=1}^{t} (P_{\tau}^A \eta_{\tau}^A \Delta t + E_{\tau}^{A,\text{arr}} - E_{\tau}^{A,\text{dep}}) \\
+ \sum_{\tau=1}^{t} C^-_{\tau} \max_k (e^-_{k\tau}) \eta_{\tau}^A \Delta t - \sum_{\tau=1}^{t} C^+_{\tau} \min_k (e^+_{k\tau}) \eta_{\tau}^A \Delta t \\
\leq E_{t}^{A,\text{max}} - \Delta E^A + \min_k \left( \omega_{kt}^{A,\text{min,free}} + \sum_{\tau=1}^{t} (\omega_{k\tau}^{E,\text{dep}} - \omega_{k\tau}^{E,\text{arr}}) \right), \quad \forall t,
\]  
(4.20)

\[
E_{t}^{A,\text{min,free}} + \max_k \left( \omega_{kt}^{E,\text{min,free}} + \sum_{\tau=1}^{t} (\omega_{k\tau}^{E,\text{dep}} - \omega_{k\tau}^{E,\text{arr}}) \right) \\
\leq \sum_{\tau=1}^{t} (P_{\tau}^A \eta_{\tau}^A \Delta t + E_{\tau}^{A,\text{arr}} - E_{\tau}^{A,\text{dep}}) - \Delta E^A \\
+ \sum_{\tau=1}^{t} C^-_{\tau} \min_k (e^-_{k\tau}) \eta_{\tau}^A \Delta t - \sum_{\tau=1}^{t} C^+_{\tau} \max_k (e^+_{k\tau}) \Delta t / \eta_{\tau}^A, \quad \forall t.
\]  
(4.21)

Compared with the unidirectional case, \( P_{t}^{A,\text{max,free}} \) and \( P_{t}^{A,\text{min,free}} \) are replaced by \( P_{t}^{A,\text{min,V2G}} \) and \( P_{t}^{A,\text{max,V2G}} \). Therefore, the dimension of the hyper-rectangle is also \( n^{\text{hr}} = 9T \) and the number of bounds to be computed is \( 11T \) (or \( 4T \) without driving pattern uncertainty), so (4.15) applies.

**Constraints on reserve capacities**

Further, it is important to explore restrictions that possibly apply to the offered reserve capacities. Two such restrictions are typically:

- **Symmetric capacities:**
  \[ C_t := C_t^- = C_t^+, \quad \forall t \]  
(4.22)

- **Constant capacities:**
  \[ C^- := C_{(t=1)}^- = \ldots = C_{(t=T)}^-, \quad C^+ := C_{(t=1)}^+ = \ldots = C_{(t=T)}^+ \]  
(4.23)
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Constraints (4.11)-(4.14) are reformulated in the following for these special cases, which reduces the conservativeness of the adopted robust approach. The same procedure can be followed for the constraints with V2G (4.6)-(4.9). The corresponding formulation is left out for brevity.

Reformulation of joint chance constraint – symmetric capacities

In the case of symmetric capacities, only the normalized energy requests $e_{kt} = e_{kt}^+ - e_{kt}^-$ need to be considered, which can take positive or negative values. Therefore, because $\max_k(e_{kt}^+ - e_{kt}^-) \leq \max_k(e_{kt}^+) - \min_k(e_{kt}^-)$ holds, the approach becomes less conservative with respect to the uncertainty.

\[
P^A_t + C_t \leq P^A_{t,\text{max, free}} + \min_k(\omega^A_{kt,\text{max, free}}), \quad \forall t, \quad (4.24)
\]

\[
P^A_{t,\text{min, free}} + \max(\omega^A_{kt,\text{min, free}}) \leq P^A_t - C_t, \quad \forall t, \quad (4.25)
\]

\[
\sum_{\tau=1}^{t} (P^A_{\tau} \eta^A_{\tau} \Delta t + E^A_{\tau,\text{arr}} - E^A_{\tau,\text{dep}}) - \Delta E^A - \sum_{\tau=1}^{t} C^A_{\tau} \min_k(e_{k\tau}) \eta^A_{\tau} \Delta t \\
\leq E^A_{t,\text{max}} + \min_k \left( \omega^A_{kt,\text{max}} + \sum_{\tau=1}^{t} \left( \omega^A_{k\tau,\text{dep}} - \omega^A_{k\tau,\text{arr}} \right) \right), \quad \forall t, \quad (4.26)
\]

\[
E^A_{t,\text{min, free}} + \max_k \left( \omega^A_{kt,\text{min, free}} + \sum_{\tau=1}^{t} \left( \omega^A_{k\tau,\text{dep}} - \omega^A_{k\tau,\text{arr}} \right) \right) \\
\leq \sum_{\tau=1}^{t} (P^A_{\tau} \eta^A_{\tau} \Delta t + E^A_{\tau,\text{arr}} - E^A_{\tau,\text{dep}}) - \Delta E^A \quad (4.27)
\]

\[
- \sum_{\tau=1}^{t} C_{\tau} \max_k(e_{k\tau}) \eta^A_{\tau} \Delta t, \quad \forall t.
\]

In this case, the uncertain inputs whose upper and lower bounds define the hyper-rectangle are those corresponding to the variables related to driving pattern uncertainty ($\omega$-variables) and the upper and lower bound of $e_t$ for all $t$.

Therefore, the dimension of the hyper-rectangle is $n^{hr} = 8T$ and the number of bounds to be computed is reduced to $9T$ (or $2T$ without
driving pattern uncertainty), which imposes the condition

\[
K \geq \left\lceil \frac{1}{\epsilon} \frac{e}{e - 1} \left( 9T - 1 + \ln \frac{1}{\beta} \right) \right\rceil \tag{4.28}
\]
on the number of samples that needs to be extracted.

**Reformulation of joint chance constraint – constant capacities**

In the case of capacities that are constant throughout the time horizon, the fact that the worst-case energy requests do not necessarily come consecutively, i.e. \(\max_k (\sum_{\tau=1}^{t} e_{k\tau}^-) \leq \sum_{\tau=1}^{t} \max_k e_{k\tau}^-\) can be exploited.

\[
P_t^A + C^- \leq P_{t}^{A,\text{max,free}} + \min_k (\omega_{kt}^{A,\text{max,free}}), \quad \forall t, \tag{4.29}
\]

\[
P_{t}^{A,\text{min,free}} + \max_k (\omega_{kt}^{A,\text{min,free}}) \leq P_t^A - C^+, \quad \forall t, \tag{4.30}
\]

\[
\sum_{\tau=1}^{t} (P_{\tau}^A \eta_{\tau}^A \Delta t + E_{\tau}^A,\text{arr} - E_{\tau}^A,\text{dep}) - \Delta E^A
\]

\[
+ C^- \max_k (\sum_{\tau=1}^{t} e_{k\tau}^- \eta_{\tau}^A) \Delta t - C^+ \min_k (\sum_{\tau=1}^{t} e_{k\tau}^+ \eta_{\tau}^A) \Delta t
\]

\[
\leq E_{t}^{A,\text{max}} + \min_k \left( \omega_{kt}^{A,\text{max}} + \sum_{\tau=1}^{t} (\omega_{k\tau}^{A,\text{dep}} - \omega_{k\tau}^{A,\text{arr}}) \right), \quad \forall t, \tag{4.31}
\]

\[
E_{t}^{A,\text{min,free}} + \max_k \left( \omega_{kt}^{A,\text{min,free}} + \sum_{\tau=1}^{t} (\omega_{k\tau}^{A,\text{dep}} - \omega_{k\tau}^{A,\text{arr}}) \right)
\]

\[
\leq \sum_{\tau=1}^{t} (P_{\tau}^A \eta_{\tau}^A \Delta t + E_{\tau}^A,\text{arr} - E_{\tau}^A,\text{dep}) - \Delta E^A
\]

\[
+ C^- \min_k (\sum_{\tau=1}^{t} e_{k\tau}^- \eta_{\tau}^A) \Delta t - C^+ \max_k (\sum_{\tau=1}^{t} e_{k\tau}^+ \eta_{\tau}^A) \Delta t, \quad \forall t. \tag{4.32}
\]

In this case, the uncertain inputs whose upper and lower bounds define the hyper-rectangle are those corresponding to the variables related to driving pattern uncertainty (\(\omega\text{-variables}\)) and:

- Upper and lower bound of \(\sum_{\tau=1}^{t} e_{k\tau}^+ \eta_{\tau}^A\) for all \(t\).
• Upper and lower bound of \( \sum_{\tau=1}^{t} \epsilon_{k\tau}^{-} \eta_{\tau}^{A} \) for all \( t \).

Therefore, the dimension of the hyper-rectangle is \( n^{hr} = 9T \) and the number of bounds to be computed is \( 11T \) (or \( 4T \) without driving pattern uncertainty), as in the original case without constraints on the reserve capacities.

**Reformulation of joint chance constraint – symmetric and constant capacities**

In the case of symmetric and constant capacities \( C \), both of the simplifications above apply.

\[
P_{t}^{A} + C \leq P_{t}^{A,\text{max,free}} + \min_{k}(\omega_{kt}^{P_{t}^{A,\text{max,free}}}), \quad \forall t, \quad (4.33)
\]

\[
P_{t}^{A,\text{min,free}} + \max_{k}(\omega_{kt}^{P_{t}^{A,\text{min,free}}}) \leq P_{t}^{A} - C, \quad \forall t, \quad (4.34)
\]

\[
\sum_{\tau=1}^{t} (P_{\tau}^{A} \eta_{\tau}^{A} \Delta t + E_{\tau}^{A,\text{arr}} - E_{\tau}^{A,\text{dep}}) - \Delta E^{A} - C \min_{k}(\sum_{\tau=1}^{t} e_{k\tau}^{-} \eta_{\tau}^{A}) \Delta t 
\]

\[
\leq E_{t}^{A,\text{max}} + \min_{k} \left( \omega_{kt}^{E_{t}^{A,\text{max}}} + \sum_{\tau=1}^{t} \left( \omega_{k\tau}^{E_{t}^{A,\text{dep}}} - \omega_{k\tau}^{E_{t}^{A,\text{arr}}} \right) \right), \quad \forall t, \quad (4.35)
\]

\[
E_{t}^{A,\text{min,free}} + \max_{k} \left( \omega_{kt}^{E_{t}^{A,\text{min,free}}} + \sum_{\tau=1}^{t} \left( \omega_{k\tau}^{E_{t}^{A,\text{dep}}} - \omega_{k\tau}^{E_{t}^{A,\text{arr}}} \right) \right)
\]

\[
\leq \sum_{\tau=1}^{t} (P_{\tau}^{A} \eta_{\tau}^{A} \Delta t + E_{\tau}^{A,\text{arr}} - E_{\tau}^{A,\text{dep}}) - \Delta E^{A} 
\]

\[-C \max_{k}(\sum_{\tau=1}^{t} e_{k\tau}^{-} \eta_{\tau}^{A}) \Delta t, \quad \forall t. \quad (4.36)\]

In this case, the uncertain inputs whose upper and lower bounds define the hyper-rectangle are those corresponding to the variables related to driving pattern uncertainty (\( \omega \)-variables) and the upper and lower bound of \( \sum_{\tau=1}^{t} e_{k\tau}^{-} \eta_{\tau}^{A} \) for all \( t \).

Therefore, the dimension of the hyper-rectangle is \( n^{hr} = 8T \) and the number of bounds to be computed is \( 9T \) (or \( 2T \) without driving pattern uncertainty), as in the case with symmetric reserve capacities.
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Constraint on the final energy content

As defined in the basic virtual battery model with equality (2.38), it is desirable that the energy at the beginning of the optimization horizon differs from that at the end of the horizon as little as possible. Including the expected deviations due to the reserve requests, $e_t^+$ and $e_t^-$, in the equation yields,

$$\sum_t \left( P_t^A \eta_t^A \Delta t - C_t^+ e_t^+ + C_t^- e_t^- + E_t^{A,\text{arr}} - E_t^{A,\text{dep}} \right) = \text{med} \sum_t \left( \omega_t^{E_{\text{dep}}^{A}} - \omega_t^{E_{\text{arr}}^{A}} \right), \forall n.$$  \hfill (4.37)

The idea is that if the reserve requests are biased, or if the aggregator tends to offer reserves asymmetrically, then this is to be compensated by either more or less regular charging $P_t^A$. The average energy requests $e_t^+$ and $e_t^-$ can be computed out of the $K$ extracted samples, i.e.

$$e_t^+ = \sum_k e_{kt}^+ / K, \quad e_t^- = \sum_k e_{kt}^- / K,$$  \hfill (4.38)

or from an available time series.

4.2.2 Bilevel model with co-optimization of regulation and day-ahead markets

The bidding strategy with co-optimization of regulation and day-ahead markets is formulated as a bilevel problem [29]. In the upper level problem, the aggregator minimizes the costs of purchasing electricity subject to the virtual battery constraints described above,

$$\begin{align*}
\min_{\Phi_{UL}, \Phi_{LL}} & \sum_t (\lambda_t P_t^A \Delta t - g_t^+ C_t^+ - g_t^- C_t^-) \\
\text{s.t.} & \quad C_t^- \geq 0, \quad C_t^+ \geq 0, \quad \forall t, \\
& \quad (4.11)-(4.14), (4.37), (3.7), \quad \forall t, \\
& \quad (4.39a)-(4.39d), (4.40)
\end{align*}$$

with decision variables for the upper level problem

$$\Phi_{UL} = \{\{c_t^A, C_t^+, C_t^-\} \forall t; E_t^{A}_{(t=0)}; \Delta E\}.$$  \hfill (4.40)
Compared with the bilevel problem (3.5), the objective function now includes the capacity payment from offering up- and down-reserves, and the constraints describing the virtual battery are different, see §4.2.1. The reserve prices \( g_t^+ \) and \( g_t^- \) paid to the aggregator (capacity payments) are considered exogenous, i.e. it is assumed that the aggregator does not have market power in the capacity market. If this assumption is not justified, another lower level problem reflecting the clearing of the regulation market could be introduced. The market clearing price \( \lambda_t \) and the accepted volume of the aggregator’s bid \( P_A^t \), stem from the solution of the market clearing problem (3.7) for each time step \( t \) introduced in §3.3.1. Apart from the capacity remuneration, typically there is also a remuneration for energy. In Switzerland, the energy remuneration is a function of the day-ahead market prices. Therefore, including this component would add a bilinear term to the objective function, since the day-ahead prices are endogenous parameters. Because the energy remuneration is expected to be one order of magnitude lower than the capacity remuneration [29], the energy term is omitted in the objective function.

As in §3.3.2 several scenarios for the lower level can be considered. The decision variables of the upper level are then

\[
\Phi_{ULs} = \{ c_{rt}^A, \forall t, \forall r; \{ C_t^+, C_t^- \} \forall t; E_A^{t=0}; \Delta E \}. \tag{4.41}
\]

To transform the bilevel problem into a Mixed Integer Linear Programming (MILP) problem, the same procedure as in §3.3 is adopted. First, the lower level is replaced by its Karush-Kuhn-Tucker (KKT) constraints. Second, linear reformulations are established for the complementarity constraints and for the objective function.

In summary, the problem can be formulated as the following MILP problem.

\[
\begin{align*}
\text{Min.} & \quad \sum_r \pi_r \sum_t K_{rt} - \sum_t (g_t^+ C_t^+ + g_t^- C_t^-) \tag{4.42a} \\
\text{s.t.} & \quad C_t^- \geq 0, \quad C_t^+ \geq 0, \quad \forall t, \tag{4.42b} \\
& \quad (4.11)-(4.14), (4.37), \tag{4.42c} \\
& \quad (3.15), (3.16), (3.18)-(3.20), \tag{4.42d} \\
& \quad \Phi_{cur} \in \{0,1\}, \Phi_{aux} \in \{0,1\}. \tag{4.42e}
\end{align*}
\]
4.2. Centralized reserve scheduling

Constraints (4.11)-(4.14), (4.37), which are valid for the general case without V2G, can be replaced by the corresponding constraints when V2G is available, or when constraints on the offered reserve capacities apply, see §4.2.1.

4.2.3 Wind forecast error balancing

The previous subsection deals with a co-optimization between the day-ahead and the regulation market. In general, the aggregator can trade off between purchasing energy at minimum cost and offering one or more ancillary service(s), either on a specific market or through bilateral contracts. In the context of an increasing penetration of RES whose output is weather-dependent, an interesting service is the use of PEV charging (and discharging) flexibility to compensate the forecast errors of a group of RES. Here the focus is on wind power.

The self-scheduling problem of a PEV aggregator who bids in the day-ahead market to purchase energy on behalf of a PEV fleet, and, at the same time, enters a bilateral contract with an operator of wind power plants, is considered [48]. According to this contract, the aggregator has to balance a fraction of the operator’s wind output forecasting errors (with respect to the day-ahead forecast) during the next day. This problem is very similar to the co-optimization problem between day-ahead and regulation markets described in §4.2.2. The requests for regulation correspond in this context to requests to compensate the forecast error. The reserve capacities $C_t$ are now interpreted as the wind capacity whose forecast error is to be compensated, and the energy requests $e_t$ are interpreted as the average forecast error during time step $t$ normalized by the total wind capacity. As in the previous case, it is possible to split the capacities into up-reserves $C^+_t$ (when the forecast exceeds the wind output) and down-reserves $C^-_t$ (when the wind output exceeds the forecast). The energy constraints remain unchanged with respect to the ones described in §4.2.1 only with a different interpretation of the parameters. However, the power constraints need to be slightly modified. Whereas for the energy constraints the average errors during each time step are considered, for the power constraints a worst-case approach is adopted. This is similar to the assumption in §4.2.1 that the full contracted regulation capacity must be available power-wise, see, e.g. (4.2),(4.3). In the case of wind balancing, for down-reserves, the worst-case occurs when the wind power plants produce their maximum
output instead of producing the forecasted value. For up-reserves, the worst case occurs when the wind power plants do not produce at all. If $f_t$ is the normalized forecasted power output for time $t$, then the power constrains can be written as

$$P_t^A + C_t^- (1 - f_t) \leq P_t^{A,max,free} + \min_k (\omega_{kt}^P_{A,max,free}), \quad \forall t, \quad (4.43)$$

$$P_t^{A,min,free} + \max_k (\omega_{kt}^P_{A,min,free}) \leq P_t^A - C_t^+ f_t, \quad \forall t. \quad (4.44)$$

Apart from these differences in the formulation of the power constrains, the co-optimization problems in this section and the previous section have an identical structure. However, the statistical characteristics of the regulation requests and the forecast error are different. In particular, for RES, the forecast error, and the corresponding balancing requests, are a function of the forecasted value (conditional probability). More details on this are given in §4.4 which deals with the generation of service request scenarios.

Note that a probabilistic approach is chosen for the cumulative energy deviations, whereas a worst-case approach is used for the power deviations. The idea is that, for a very short period of time, the PEV aggregator might have to deal with the worst possible situation. It would also be possible to adopt a probabilistic approach for the power deviations, but only hourly wind data was available for this work.

### 4.3 Decentralized reserve scheduling

The optimization problem (3.29)-(3.30) is extended to take into account the scheduling of ancillary services in addition to the scheduling of the regular charging profiles. The focus here is on the case of symmetric reserves, but the framework can be readily extended to the case of asymmetric reserves. Only unidirectional charging is considered in this case (no V2G).
4.3. Decentralized reserve scheduling

4.3.1 Optimal charging and reserve scheduling formulation

The fleet commits the symmetric reserve capacity $c \in \mathbb{R}^T$, that is equal to the sum of the individual reserve capacities $r_{kv} \in \mathbb{R}^T$ of vehicles $v$ (in all $k$ scenarios) and thereby earns $e^R(c)$ capacity revenues. There is a tradeoff between the costs associated with purchasing the charging energy $c^E(\cdot)$ and the revenues from providing reserves $e^R(\cdot)$. The charging and reserve scheduling problem can be written as

$$\text{Min}_{\Phi_{RD}} \sum_k \frac{1}{K} c^E(l_k, P_k^D, P_k^S) - e^R(c)$$  \hspace{1cm} (4.45a)

subject to:

$$l_k = \sum_v x_{kv}, \quad \forall k,$$  \hspace{1cm} (4.45b)

$$c = \sum_v r_{kv}, \quad \forall k,$$  \hspace{1cm} (4.45c)

$$x_{kv(t=1)} = x_{k'v(t=1)}, \quad \forall v, \forall k, k' \in K$$  \hspace{1cm} (4.45d)

$$Ax_{kv} + Br_{kv} \leq b_{kv}, \quad \forall v, \forall k,$$  \hspace{1cm} (4.45e)

$$x_{kv}^{\text{min}} \leq x_{kv} - r_{kv}, \quad x_{kv} + r_{kv} \leq x_{kv}^{\text{max}}, \quad \forall v, \forall k,$$  \hspace{1cm} (4.45f)

$$0 \leq r_{kv}, \quad \forall v, \forall k,$$  \hspace{1cm} (4.45g)

with decision variables

$$\Phi_{RD} = (x_k, \forall k; l_k, \forall k; P_k^D, \forall k; P_k^S, \forall k; r_k, \forall k; c).$$

An important difference between the way the total load $l_k$ and the total reserve capacity $c$ are treated is that the reserves are not allowed to be scenario-dependent: At each scenario $k$, the sum of individual reserve capacities $r_{kv}$ needs to be equal to the same $c$ (4.45c). This is because reserves should be provided with high reliability. The energy and power constraints, (4.45e) and (4.45f) respectively, now also take into account the deviations from the reference profiles that can be caused by deploying the committed reserves. This is discussed in detail in §4.2.1 for the aggregated battery model, and can be readily applied to the individual model too. In particular, (4.45e) corresponds to the constraints

$$\sum_{\tau=1}^{t} \left( P_{v\tau}^V + \max_k (e_{k\tau}) r_{v\tau} \right) n_{v}^V \Delta t - E_{v\tau}^{V,\text{cons}} \leq C_{v}^V \text{SOC}_{v}^{V,\text{max}}, \quad \forall v, \forall t$$  \hspace{1cm} (4.46)
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\[ C_v^{V, \text{SOC}_{v, \text{min}}} \leq \sum_{\tau=1}^{t} \left( \left( P_{\nu\tau}^{V} + \min_k (e_k r_{\nu\tau}) \right) \eta_v^V \Delta t - E_{\nu\tau}^{V, \text{cons}} \right), \quad \forall v, \forall t \]  

(4.47)

\[ \sum_{\tau=1}^{T} \left( \left( P_{\nu\tau}^{V} + e_{\tau} r_{\nu\tau} \right) \eta_v^V \Delta t - E_{\nu\tau}^{V, \text{cons}} \right) = 0, \quad \forall v. \]  

(4.48)

These constraints at the individual level are the counterpart of (4.26) (4.27) (4.37) at the aggregated level. Constraint (4.45f) is the counterpart of the power constraints (4.24) (4.25).

4.3.2 Solving the optimal charging and reserve scheduling problem with ADMM

Problem reformulation

By introducing the auxiliary decision variables \( \tilde{x}_k \in \mathbb{R}^{T \times V}, \tilde{l}_k \in \mathbb{R}^T, \tilde{r}_k \in \mathbb{R}^{T \times V}, \) and \( \tilde{c}_k \in \mathbb{R}^T, \) the optimization problem (4.45) can be formulated as the equivalent problem

\[ \min_{\Phi^{RD}, \tilde{\Phi}^{RD}} \sum_k \frac{1}{K} c^E(l_k, P_k^D, P_k^S) - c^R(c) + \sum_{k,v} g_{kv}(x_{kv}) + f(\tilde{x}, \tilde{l}, \tilde{r}, \tilde{c}) \]

s.t. \( x_k = \tilde{x}_k, \forall k, \)

\( l_k = \tilde{l}_k, \forall k, \)

\( r_k = \tilde{r}_k, \forall k, \)

\( c = \tilde{c}_k, \forall k. \)

The function \( g_{kv}(x_{kv}) \) is the indicator function on the set defined by the constraints (4.45e)-(4.45g) and \( f(\tilde{x}, \tilde{l}, \tilde{r}, \tilde{c}) \) is the indicator function on the set defined by the constraints (4.45b)-(4.45d), now applied to the duplicated variables.

As in §3.4.2 the problem above exhibits the two-part structure suitable for ADMM, with \( \Phi^{RD} \) and \( \tilde{\Phi}^{RD} = (\tilde{x}_k, \forall k; \tilde{l}_k, \forall k; \tilde{r}_k, \forall k; \tilde{c}_k, \forall k) \) the first and second block of variables, respectively.
The augmented Lagrangian of this optimization problem is

\[
L_\rho(\Phi^{RD}, \tilde{\Phi}^{RD}, u, w, p, q) = \sum_k \frac{1}{K} c(l_k, P^D_k, P^S_k) - e^R(c) + \sum_{kv} g_{kv}(x_{kv}) + f(\tilde{x}, \tilde{l}, \tilde{x}, \tilde{l})
+ \rho \sum_{kv} \|x_{kv} - \tilde{x}_{kv} + u_{kv}\|_2^2
+ \rho \sum_{k} \|l_k - \tilde{l}_k + w_k\|_2^2,
+ \rho \sum_{kv} \|r_{kv} - \tilde{r}_{kv} + p_{kv}\|_2^2
+ \rho \sum_{k} \|c - \tilde{c}_k + q_k\|_2^2,
\]

with the scaled dual variables \(w = (w_k, \forall k)\), \(u = (u_k, \forall k)\), with \(u_k = (u_{kv}, \forall v)\), \(q = (q_k, \forall k)\), \(p = (p_k, \forall k)\), with \(p_k = (p_{kv}, \forall v)\). To obtain the unscaled dual variables, the scaled dual variables need to be multiplied with the penalty parameter \(\rho\).

**ADMM algorithm**

The steps at each iteration of the ADMM algorithm are shown in Table 4.1. Here, the overline on variables \(x_v, u_v, i\) and \(d\) is used to denote the mean across samples, e.g. \(\bar{x}_v := 1/K \sum_k x_{kv}\).

The \(\Phi^{RD}\)-minimization step is carried out by all PEVs and the aggregator in parallel, which can also solve each scenario in parallel. Then, the charging and reserve schedules are communicated to the aggregator, which computes the imbalance \(i^E_k\) between the sum of individual charge profiles and the aggregated profile, and the imbalance \(i^R_k\) between the sum of individual reserve offers and the aggregated reserve offer, both normalized by the number of agents \((V + 1)\). The value of the imbalances is communicated to the vehicles. With this information, the agents perform the \(\tilde{\Phi}^{RD}\)-minimization step in parallel (algebraic operations), and, subsequently, the dual update in parallel. Finally, the value of \(\bar{d}(t=1)\) is calculated by the aggregator, based on the dual variables communicated by the vehicles. This value is used by the agents in the \(\tilde{\Phi}^{RD}\)-minimization step of the following iteration.
Table 4.1: ADMM algorithm steps at each iteration.

<table>
<thead>
<tr>
<th>Step Description</th>
<th>Mathematical Formulation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Φ</strong>&lt;sup&gt;RD&lt;/sup&gt;-minimization step (for each agent/scenario in parallel):</td>
<td></td>
</tr>
<tr>
<td>( (x_{kv}, r_{kv})^{m+1} := )</td>
<td>[ \argmin_{x_{kv}, r_{kv}} \left( g_{kv}(x_{kv}) + \frac{\rho}{2} | x_{kv} - x_{kv}^{m} + u_{kv}^{m} |<em>2^2 + \frac{\rho}{2} | r</em>{kv} - \tilde{r}<em>{kv}^{m} + p</em>{kv}^{m} |_2^2 \right) \forall v, \forall k ]</td>
</tr>
<tr>
<td>((l_k, P_k^D, P_k^S)^{m+1} := )</td>
<td>[ \argmin_{l_k, P_k^D, P_k^S} \left( \frac{1}{k} \sum_{v} c^E(l_k, P_k^D, P_k^S) + \frac{\rho}{2} | l_k - \tilde{l}<em>{k}^{m} + w</em>{kv}^{m} |_2^2 \right) \forall k ]</td>
</tr>
<tr>
<td>(c^{m+1} := \argmin_c \left( -e^R(c) + \frac{\rho}{2} | c - \tilde{c}_k^{m} + q_k^{m} |_2^2 \right) \forall k )</td>
<td></td>
</tr>
<tr>
<td><strong>Schedule aggregation (for each scenario in parallel):</strong></td>
<td></td>
</tr>
<tr>
<td>( \gamma_{E,k(t=1)}^{m+1} := \gamma_{E,k(t=1)}^{m+1} + \bar{w}<em>{v(t=1)}^{m} - \bar{d}</em>{v(t=1)}^{m} ) \forall v, \forall k</td>
<td></td>
</tr>
<tr>
<td>( \gamma_{k(t=1)}^{m+1} := \gamma_{k(t=1)}^{m+1} + \mu_{E,k(t=1)}^{m+1} ) \forall v, \forall k, \forall t &gt; 1</td>
<td></td>
</tr>
<tr>
<td>( \rho_{k(t=1)}^{m+1} := \rho_{k(t=1)}^{m+1} + \mu_{E,k(t=1)}^{m} ) \forall k, \forall t &gt; 1</td>
<td></td>
</tr>
<tr>
<td>( \rho_{k(t=1)}^{m+1} := \rho_{k(t=1)}^{m+1} ) \forall k</td>
<td></td>
</tr>
<tr>
<td>( \tilde{c}_k^{m+1} := \tilde{c}<em>k^{m+1} + \tilde{r}</em>{k(t=1)}^{m+1} \forall v, \forall k</td>
<td></td>
</tr>
<tr>
<td><strong>Dual variable update (for each agent/scenario in parallel):</strong></td>
<td></td>
</tr>
<tr>
<td>( u_{kv(t=1)}^{m+1} := u_{kv(t=1)}^{m} + x_{kv(t=1)}^{m+1} - \tilde{x}_{kv(t=1)}^{m+1} ) \forall v, \forall k</td>
<td></td>
</tr>
<tr>
<td>( w_k^{m+1} := w_k^{m} + l_k^{m+1} - \tilde{l}_k^{m+1} ) \forall k</td>
<td></td>
</tr>
<tr>
<td>( p_k^{m+1} := p_k^{m} + r_{kv(t=1)}^{m+1} - \tilde{r}_{kv(t=1)}^{m+1} \forall v, \forall k</td>
<td></td>
</tr>
<tr>
<td>( q_k^{m+1} := q_k^{m} + c^{m+1} - \tilde{c}_k^{m+1} ) \forall k</td>
<td></td>
</tr>
<tr>
<td><strong>Dual variable aggregation:</strong></td>
<td>[ \tilde{d}<em>{k(t=1)}^{m+1} := 1/K \sum_k \left( \sum_v u</em>{kv(t=1)}^{m+1} - u_{k(t=1)}^{m+1} \right) / (V + 1) ]</td>
</tr>
</tbody>
</table>

**Convergence**

As explained in §3.4.2, when the objective functions of the aggregator and vehicles are closed, proper, and convex, and a solution to the problem exists, there is convergence of the objective, residuals and dual variables.

The stopping criterion is defined based on the norms of the primal \( r^m \) and dual \( s^m \) residuals computed at iteration \( m \),
4.4 Generating scenarios of service requests

\[ \|r^{m+1}\|_2^2 = + \sum_{kv} \|x_{kv}^{m+1} - \tilde{x}_{kv}^{m+1}\|_2^2 + \sum_k \|l_k^{m+1} - \tilde{l}_k^{m+1}\|_2^2 \\
+ \sum_{kv} \|r_{kv}^{m+1} - \tilde{r}_{kv}^{m+1}\|_2^2 + \sum_k \|c_k^{m+1} - \tilde{c}_k^{m+1}\|_2^2, \]

\[ \|s^{m+1}\|_2^2 = + \sum_{kv} \|\tilde{x}_{kv}^{m+1} - \tilde{x}_{kv}^m\|_2^2 + \sum_k \|\tilde{l}_k^{m+1} - \tilde{l}_k^m\|_2^2 \\
+ \sum_{kv} \|\tilde{r}_{kv}^{m+1} - \tilde{r}_{kv}^m\|_2^2 + \sum_k \|\tilde{c}_k^{m+1} - \tilde{c}_k^m\|_2^2. \]

The termination criterion proposed in [133, §3.3] is applied.

4.4 Generating scenarios of service requests

In §4.2.1 the virtual battery constraints were described, which, among other inputs, require scenarios of service requests as an input. To obtain samples of the wind power prediction error, the method in [160], capable of generating stochastic samples of short-term wind generation, is used. This method takes the interdependence structure of the prediction errors and the predictive distribution of the wind power production into account. The goal is to generate \( K \) scenarios of possible wind power outputs given a day-ahead wind power output forecast. The steps below are followed to obtain the scenarios:

1. The probability distributions of the wind power output for each hour of the next day are estimated. A non-parametric distribution is obtained from quantile regressions using the wind forecast as explanatory variable. Past pairs of data of the forecasted and realized power output are used in the regression.

2. The series of wind power outputs is transformed into a multivariate Gaussian random variable using the distributions determined in the first step. The corresponding covariance matrix is calculated.
3. $N$ samples of multivariate Gaussian random variables can be extracted and converted back to the original wind power output distribution. Out of the $N$ extracted wind power output realizations, the corresponding values of the forecast error are derived.

To obtain scenarios for the regulation reserve requests, a similar approach is followed. However, in the first step, it is not necessary to perform a quantile regression, since there are no explanatory variables. Instead, the quantiles are determined to obtain the non-parametric probability distribution of the regulation reserve requests.

## 4.5 Case study

In the following, a case study based on Swiss frequency regulation, market, and transportation data, as well as wind data from the National Renewable Energy Laboratory (NREL), is presented, where the methods described in this chapter are compared and analyzed.

First, the inputs to the case study are described (§4.5.1). Then, the results of the centralized scheduling to provide regulation reserves (§4.5.2), and wind forecast error balancing (§4.5.3) are discussed. Finally, the results of the decentralized scheduling are reported (§4.5.4).

### 4.5.1 Case study setup

This case study is based on the same data as the case study in the previous chapter and focuses on the same week in 2013 (21-27/10/13), see §3.9. Here, only the additional data inputs and assumptions are detailed.

**Frequency regulation data**

A time series of the secondary frequency control signal (AGC signal) for one year, sampled every 10 seconds, was obtained from the Swiss TSO, Swissgrid. Fig. 4.2 shows the empirical Cumulative Distribution Function (CDF) of the normalized hourly energy requests. The hourly requests are typically small (in 80% of the cases, they are smaller than
0.18 for up regulation and smaller than 0.26 for down regulation), which is one of the reasons for low energy revenues. However, there are a number of samples with values close to the maximum, i.e. close to one. Moreover, there is a bias towards down regulation, see Fig. 4.2c which for PEVs means additional charging on average, if symmetric capacities are offered.

![Cumulative probability graphs](image)

**Figure 4.2:** Empirical cumulative distribution functions of the hourly normalized regulation requests (across all hours).

The capacity in the Swiss regulation market is remunerated on a pay-as-bid basis. The TSO asks for a total symmetric capacity of around 400 MW \[161\]. Fig. 4.3 shows the day-ahead market prices and the average regulation capacity prices \[162\] for the year 2013. At the beginning of the spring, regulation prices are very high compared with day-ahead

\[5\] The regulation capacity prices are published in Swiss francs (CHF). Here, the conversion rate of 1.23 CHF/€ is used, which was the average rate for 2013 (with variance < 10\(^{-4}\)) \[162\].
prices. This is because, in the Swiss system, regulation is mainly provided by hydro power plants. The regulation prices therefore depend on the content of the hydro reservoirs, which typically reach a minimum before the snowmelt begins. The empirical CDF of the published regulation prices is displayed in Fig. 4.4. Most of the time (82%), the prices lie between 15 and 30 €/MW/h, but also some higher price spikes exist, that go almost up to 300 €/MW/h.

The published regulation prices are not directly used in the simulations, but the results are computed for a range of prices. The prices published by the TSO are for symmetric offers of up and down regulation capacities, so to compare these to the prices $g_t^+ = g_t^-$ defined in the co-optimization problem, the published prices should be divided by two to characterize the prices of each component. Therefore, the interesting range for $g_t^+ = g_t^-$ is particularly 7.5-15 €/MW/h and in general up to 150 €/MW/h.

Currently, regulation bids in Switzerland are symmetric, and a constant capacity is offered for a full week [161]. Here, since each day is simulated separately, when bids are forced to be constant, this is applied to a single day only.

![Figure 4.3: Average regulation capacity prices and day-ahead market prices in Switzerland 2013. The displayed regulation capacity prices are for symmetric bids.](image)

**Wind data**

Wind output and day-ahead forecast data was obtained from NREL. The analyzed wind power forecast profiles are displayed in Fig. 4.5 together with the actual realization profiles, and 1000 scenarios generated
4.5. Case study

![Empirical cumulative distribution function of the average regulation capacity prices in Switzerland 2013. The displayed regulation capacity prices are for symmetric bids.]

**Figure 4.4:** Empirical cumulative distribution function of the average regulation capacity prices in Switzerland 2013. The displayed regulation capacity prices are for symmetric bids.

with the method described in §4.4. Seven different daily profiles (corresponding to one week) are considered. Each of the profiles is combined with each of the days of the simulated week (7x7 combinations). Some days have increasing wind profiles (one, five and six), others decreasing profiles (three and seven), and others (two and four) flatter profiles.

![Wind profiles used in the case study.]

**Figure 4.5:** Wind profiles used in the case study.

**Joint chance constraint in the centralized model**

For the joint chance constraint described §4.2 the violation parameter $\epsilon$ was set to 0.1 and the confidence parameter $\beta$ to $1e^{-7}$. The number of samples of driving patterns and regulation/balancing requests that need to be extracted are displayed in Table 4.2, see §4.2.1. This number depends on the structure of the reserve offers (unconstrained, constant, symmetric) and on whether driving patterns are assumed to be perfectly
Chapter 4. Ancillary service provision

forecasted or not. Note that in both cases, “perfect information” and “driving pattern uncertainty”, the uncertainty of regulation/balancing requests is considered.

Table 4.2: Number of samples required for the reformulation of the joint chance constraint.

<table>
<thead>
<tr>
<th></th>
<th>perfect information</th>
<th>driving pattern uncertainty</th>
</tr>
</thead>
<tbody>
<tr>
<td>unconstrained /</td>
<td>1758</td>
<td>4416</td>
</tr>
<tr>
<td>constant</td>
<td></td>
<td></td>
</tr>
<tr>
<td>symmetric /</td>
<td>999</td>
<td>3657</td>
</tr>
<tr>
<td>symmetric &amp; constant</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

ADMM parameters

Here, the parameters specific to the decentralized scheduling problem in §4.3 are defined. For the termination criterion proposed in §3.3.1, the nominal absolute and relative tolerances are set to $10^{-4}$. The algorithm is stopped in any case after 5000 iterations. The value of $\rho$ is set to 100.

For each vehicle, 200 random samples of driving patterns are generated. At each stage of the receding horizon optimization $K = 5$ samples of driving patterns are taken into account for each vehicle\(^6\).

4.5.2 Centralized scheduling of regulation reserves

Regulation capacity potential

First, the regulation capacity potentials are analyzed, i.e. the maximum capacity that the aggregator can offer independently of the remuneration. The average hourly values for up, down and total regulation are displayed in Table 4.3 for the different configurations (with/without

\(^6\)Note that in the ADMM algorithm, a much smaller number of driving pattern samples is considered than in the centralized problem. This is because it is probably not realistic to assume that the local controller at each PEV can solve a large amount of problems at a given time efficiently.
4.5. Case study

V2G, perfect information/driving pattern uncertainty, and the different settings of the regulation market). The impact of market bid uncertainty is not analyzed in this chapter.

The average hourly capacity is computed as

$$\frac{\sum_{d=1}^{D} \sum_{t=1}^{T} (C_{dt}^+ + C_{dt}^-)}{DT},$$

where \(d\) is the index for the days of the week and \(t\) the index for the hourly time steps.

<table>
<thead>
<tr>
<th></th>
<th>(C^+)</th>
<th>(C^-)</th>
<th>(C^+ + C^-)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\pi^5)</td>
<td>59.68</td>
<td>115.66</td>
<td>140.33</td>
</tr>
<tr>
<td>(\text{du}^6)</td>
<td>60.73</td>
<td>102.53</td>
<td>142.55</td>
</tr>
<tr>
<td>(\pi)</td>
<td>152.40</td>
<td>140.40</td>
<td>191.43</td>
</tr>
<tr>
<td>(\text{du})</td>
<td>127.70</td>
<td>121.45</td>
<td>150.68</td>
</tr>
<tr>
<td>(\text{no V2G})</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\pi)</td>
<td>205.17</td>
<td>115.66</td>
<td>140.33</td>
</tr>
<tr>
<td>(\text{du})</td>
<td>178.74</td>
<td>102.53</td>
<td>142.55</td>
</tr>
<tr>
<td>(\pi)</td>
<td>169.47</td>
<td>140.40</td>
<td>191.43</td>
</tr>
<tr>
<td>(\text{du})</td>
<td>153.96</td>
<td>121.45</td>
<td>150.68</td>
</tr>
<tr>
<td>(V2G)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\pi)</td>
<td>264.85</td>
<td>231.32</td>
<td>280.65</td>
</tr>
<tr>
<td>(\text{du})</td>
<td>239.46</td>
<td>205.07</td>
<td>285.10</td>
</tr>
<tr>
<td>(\pi)</td>
<td>321.87</td>
<td>280.79</td>
<td>382.87</td>
</tr>
<tr>
<td>(\text{du})</td>
<td>281.66</td>
<td>242.90</td>
<td>301.35</td>
</tr>
</tbody>
</table>

Table 4.3: Average hourly regulation capacity potential [MW].

1. \(\text{unc}\): unconstrained, i.e. no constraints apply on the regulation capacities;
2. \(\text{sym}\): symmetric capacities;
3. \(\text{cons}\): constant capacities;
4. \(\text{sym&cons}\): symmetric and constant capacities;
5. \(\pi\): perfect information;
6. \(\text{du}\): driving pattern uncertainty.

In the realistic case of driving pattern uncertainty (both with and without V2G), the largest total potential is reached for the case with constant capacities, the second largest for symmetric and constant capacities, third largest potential for the unconstrained case, and smallest potential for symmetric capacities. These results are counter-intuitive: One would expect that imposing symmetric and constant capacities should lead to the smallest potential, since it is the most restrictive...
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case. However, as discussed in §4.2.1, the assumption of constant capacities reduces the worst-case cumulative deviations from the reference energy profile due to regulation requests. In addition, assuming symmetry means that less scenarios are required for the reformulation of the chance constraint. The intuition is that, by eliminating some degrees of freedom, the deviations due to regulation requests become more predictable. Therefore, one needs to be less conservative about the uncertainty related to these requests, i.e. less extreme samples need to be considered.

For the same reason, driving pattern uncertainty can have a sizable impact on the total amount of reserves that can be provided (up to 21% reduction). In the previous chapter, the only effect of driving pattern uncertainty was a tightening of the constraints, which did not have a significant impact on the results due to the high predictability of the aggregated fleet parameters. However, driving pattern uncertainty has an indirect impact here, because a larger number of samples of regulation requests need to be considered if driving pattern uncertainty is present, see §4.2.1. When the number of samples increases, the probability of having to deal with more extreme samples also increases. Note that there is a single case where the total capacity increases with driving pattern uncertainty. This happens for the case without V2G and symmetric and constant constraints. The reason is that the expected total consumption is slightly higher under driving pattern uncertainty\textsuperscript{7}, which is of advantage when offering a constant up regulation capacity. This is because, without V2G, up regulation can only be offered by reducing the charging setpoint.

Enabling V2G does not always have an impact on the total potential as large as one could expect (5-36% increase), but it does have a large impact on the costs of providing that capacity, as discussed in the following. In almost all cases where capacities do not need to be symmetric, more down regulation is provided than up regulation.

\textsuperscript{7}This need not be the case in general. This result comes from the distribution assumptions explained in §3.9.1. For trips with a low energy consumption, the uniform distribution around the expected energy consumption value is not symmetric to avoid trips with negative consumption. For the samples extracted based on this asymmetric distribution, the average consumption is higher than the energy consumption of the reference sample.
4.5. Case study

Offered capacity as a function of remuneration

Fig. 4.6 shows the average hourly offered capacity for the simulated week as a function of the capacity price. The relevant price ranges are represented by the shaded areas in the Figure.

Without V2G, we observe the following order, in terms of total offered capacity, from highest to lowest, for low capacity prices (Fig. 4.6a): constant, no constraints, symmetric, symmetric and constant. For higher capacity prices, we observe the order seen in Table 4.3: constant, symmetric and constant, no constraints, symmetric. When the offered capacity comes close to the potential, the constraints on the capacity, which offer the advantage of predictability discussed above, play a more important role. The symmetry constraint is more limiting than the constant capacity constraint without V2G. This is because offering up regulation without V2G at a given time step implies that the consumed power is at least equal or higher than this offered capacity.

With V2G, we observe the following order, in terms of total offered capacity, from highest to lowest, for low capacity prices (Fig. 4.6b): constant, no constraints, symmetric, symmetric and constant (the latter three having very similar values). For higher capacity prices, we observe the order seen in Table 4.3: constant, symmetric and constant, no constraints, symmetric. The main difference to the case without V2G is that symmetry is a less constraining factor here at low capacity prices: Up regulation can be more flexibly offered using V2G, since discharging is possible.

Given that the total symmetric regulation capacity required in Switzerland is about 400 MW ($C^+ + C^-$ corresponds to 800 MW), PEVs (at 10% penetration, i.e. 430’000 PEVs) could provide a substantial amount of it within the relevant price ranges, even without V2G and with the current requirement of symmetric and constant capacities. Note that the total fleet capacity is 1505 MW, so up to about 20% of this capacity could be reserved as regulation capacity on average in the price range 7.5-15€/MW/h.
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Figure 4.6: Average hourly offered regulation capacity as a function of the capacity price. The shaded areas represent the relevant price ranges, 7.5-15 €/MW/h and 15-150 €/MW/h. Driving pattern uncertainty is taken into account.
Finally, the tradeoff between the charging costs, i.e. the costs of procuring energy in the day-ahead market, and the offered capacity is illustrated in Fig. 4.7. The day-ahead charging costs are normalized with the costs obtained in the previous chapter, where providing regulation was not considered. In some cases, the charging costs are actually reduced compared with that reference (normalized costs lower than 1). In fact, a substantial capacity can be offered at no additional cost. This is because the aggregator needs to buy less energy in total in the day-ahead market, since additional charging is obtained on average through the provision of down regulation, see (4.37)\(^8\). Through the additional flexibility provided by V2G, the corresponding tradeoff curves tend to be lower (lower costs) and further to the right (higher capacity) than those without V2G.

The ends of the tradeoff curves represent the capacity that would be provided even if there is no capacity payment (left end), and the maximum capacity that can be offered (right end). The intermediate points are calculated by varying the capacity price. By comparing the position of one of the ends of the curve across the curves, we recover the ranking of results discussed above. The left ends show the following order (from highest to lowest total capacity): constant, no constraints, symmetric, symmetric and constant. The right ends show the order: constant, symmetric and constant, no constraints, symmetric.

\(^8\)Note that the energy payments have not been considered here, so the results do not take into account that the energy obtained through down regulation requests needs to be paid for.
Figure 4.7: Tradeoff between offered regulation capacity (hourly average) and day-ahead charging costs. The charging costs are normalized by the charging costs without providing regulation. Driving pattern uncertainty is taken into account.
Typical profiles

Finally, some typical energy, charge and regulation capacity profiles are analyzed. The displayed results correspond to the capacity price $g_t^+ = g_t^- = 15\text{€}/\text{MW}/\text{h}$, which is at the higher end of the most common price range, and the first day of the simulated week. Figs. 4.8 and 4.9 show the power and energy profiles, respectively, without V2G, while Figs. 4.10 and 4.11 show the profiles with V2G. The corresponding average hourly offered capacities are reported in Table 4.4.

Table 4.4: Average hourly offered regulation capacity [MW] for the first day of the simulated week, assuming the capacity price $g_t^+ = g_t^- = 15\text{€}/\text{MW}/\text{h}$, and perfect information.

<table>
<thead>
<tr>
<th></th>
<th>unc$^1$</th>
<th>sym$^2$</th>
<th>cons$^3$</th>
<th>sym&amp;cons$^4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C^+$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>no V2G</td>
<td>0.00</td>
<td>107.43</td>
<td>0.00</td>
<td>129.23</td>
</tr>
<tr>
<td>V2G</td>
<td>47.25</td>
<td>139.13</td>
<td>0.00</td>
<td>191.43</td>
</tr>
<tr>
<td>$C^-$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>no V2G</td>
<td>249.21</td>
<td>107.43</td>
<td>309.11</td>
<td>129.23</td>
</tr>
<tr>
<td>V2G</td>
<td>249.21</td>
<td>139.13</td>
<td>309.11</td>
<td>191.43</td>
</tr>
<tr>
<td>$C^+ + C^-$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>no V2G</td>
<td>249.21</td>
<td>214.86</td>
<td>309.11</td>
<td>258.46</td>
</tr>
<tr>
<td>V2G</td>
<td>296.46</td>
<td>278.25</td>
<td>309.11</td>
<td>382.87</td>
</tr>
</tbody>
</table>

$^1$ unc: unconstrained, i.e. no constraints apply on the regulation capacities; $^2$ sym: symmetric capacities; $^3$ cons: constant capacities; $^4$ sym&cons: symmetric and constant capacities.

- No V2G / no constraints

The charge profile deviates from the reference profile (no regulation) by shifting part of the load from the night to the shoulder hours (Fig. 4.8a). The energy profile is shifted downwards as much as possible through $\Delta E$ (Fig. 4.9a), which allows to provide a substantial amount of down regulation. No up regulation is provided, since down regulation is more attractive for two reasons: 1) down regulation yields cheap additional charging energy through the regulation requests, and 2) up regulation requires scheduling a certain amount of charging power to be able to reduce it upon request. Because only down regulation is provided, the scheduled final energy content is lower than the initial energy content (Fig. 4.9a). The gap is expected to be bridged through the regulation requests.
• **No V2G / symmetric**

The charge profile deviates from the reference profile by spreading the load more evenly (Fig. 4.8b). This leads to a flatter energy profile (Fig. 4.9b), which allows to provide symmetric regulation capacities. The energy profile is partially shifted downwards through $\Delta E$. The scheduled charging demand is always at least as high as the offered up regulation capacity, since up regulation is provided by reducing the scheduled demand (no V2G). Because symmetric capacities are provided, the scheduled final energy content is only slightly lower than the initial energy content (Fig. 4.9b).

• **No V2G / constant**

The charge profile deviates from the reference profile by reducing the load during the night hours (Fig. 4.8c). The energy profile is shifted downwards as much as possible through $\Delta E$ (Fig. 4.9c), which allows to provide a substantial amount of down regulation. No up regulation is provided, since down regulation is more attractive. Because only down regulation is provided, the scheduled final energy content is lower than the initial energy content (Fig. 4.9c).

• **No V2G / symmetric and constant**

The charge profile deviates from the reference profile by reducing the load during the night hours, and by scheduling at least a small amount of charging power at every time step (Fig. 4.8d). This leads to a flatter energy profile (Fig. 4.9d), which allows to provide symmetric regulation capacities. The scheduled charging demand is always at least as high as the offered up regulation capacity, because up regulation is provided by reducing the scheduled demand (no V2G). Since the offered regulation capacities need to be constant throughout the day, a minimum charging power is imposed at every time step. Because symmetric capacities are provided, the scheduled final energy content is only slightly lower than the initial energy content (Fig. 4.9d).
4.5. Case study

Figure 4.8: Scheduled power profile \((P_A)\) and worst case deviations when offering regulation without V2G for the first day of the simulated week, assuming the capacity price \(g_t^+ = g_t^- = 15\,\text{€/MW/h}\), and perfect information. The reference charge profile \((P_A,\text{ref})\) when no regulation is provided is displayed for comparison.
Figure 4.9: Scheduled energy profile when offering regulation without V2G ($E^A$) for the first day of the simulated week, assuming the capacity price $g_t^+ = g_t^- = 15\,\text{€/MW/h}$, and perfect information. The worst case deviations from the scheduled energy profile are also plotted, as well as the initial energy content $E^A_{(t=0)}$. The reference energy profile ($E^A_{\text{ref}}$) when no regulation is provided is displayed for comparison.
4.5. Case study

- **V2G / no constraints**
  The charge profile deviates from the reference profile by shifting part of the load from the night to the shoulder hours (Fig. 4.10a). The energy profile is shifted downwards as much as possible through $\Delta E$ (Fig. 4.11a), which allows to provide a substantial amount of down regulation. Only a small amount of up regulation is provided, since down regulation is more attractive because it yields cheap additional charging through the regulation requests. Because more down regulation than up regulation is provided, the scheduled final energy content is lower than the initial energy content (Fig. 4.11a).

- **V2G / symmetric**
  The charge profile deviates only slightly from the reference profile by shifting part of the load from the night to the shoulder hours (Fig. 4.10b). This leads to a slightly flatter energy profile (Fig. 4.11b), which allows to provide symmetric regulation capacities. The energy shift $\Delta E$ is small in this case, to leave a large margin for deviations downwards (due to up regulation). Downward deviations become more prominent with V2G, because these are weighted with the discharging efficiency (1/0.9 instead of 0.9). Because symmetric capacities are provided, the scheduled final energy content is only slightly lower than the initial energy content (Fig. 4.11b).

- **V2G / constant**
  The charge profile deviates from the reference profile by reducing the load during the night hours (Fig. 4.10c). The energy profile is shifted downwards as much as possible through $\Delta E$ (Fig. 4.11c). No up regulation is provided, since down regulation is more attractive. Because only down regulation is provided, the scheduled final energy content is lower than the initial energy content (Fig. 4.11c).

- **V2G / symmetric and constant**
  The charge profile deviates from the reference profile by shifting part of the load from the night to the shoulder hours (Fig. 4.10d). This leads to a flatter energy profile (Fig. 4.11d), which allows to provide symmetric regulation capacities. The energy shift $\Delta E$ is
small in this case, to leave a large margin for deviations downwards (due to up regulation). Because symmetric capacities are provided, the scheduled final energy content is only slightly lower than the initial energy content (Fig. 4.11c).
4.5. Case study

\[ P_{A,\text{min},V2G} \text{ to } P_{A,\text{max},V2G} \]

- \( P^A - C^+ \)
- \( P^A + C^- \)

Figure 4.10: Scheduled power profile \((P^A)\) and worst case deviations when offering regulation with V2G for the first day of the simulated week, assuming the capacity price \( g^+_t = g^-_t = 15\text{€/MW/h} \), and perfect information. The reference charge profile \((P^A,\text{ref})\) when no regulation is provided is displayed for comparison.
Chapter 4. Ancillary service provision

\[ E^A_{\text{min}} - \Delta E^A \rightarrow E^A_{\text{max}} - \Delta E^A \]

\[ E^A - \Delta E^A \text{ worst case deviation (max)} \]

\[ E^A_{(t=0)} - \Delta E^A \]

\[ E^A_{\text{ref}} - \Delta E^A \]

\[ E^A - \Delta E^A \text{ worst case deviation (min)} \]

\[ E^A_{\text{min}} \rightarrow E^A_{\text{max}} \]

Figure 4.11: Scheduled energy profile when offering regulation with V2G \((E^A)\) for the first day of the simulated week, assuming the capacity price \(g^+_t = g^-_t = 15€/MW/h\), and perfect information. The worst case deviations from the scheduled energy profile are also plotted, as well as the initial energy content \(E^A_{(t=0)}\). The reference energy profile \((E^A_{\text{ref}})\) when no regulation is provided is displayed for comparison.
4.5.3 Centralized scheduling of wind balancing reserves

Wind forecast error balancing capacity potential

First, the wind balancing capacity potential is analyzed, i.e. the wind power capacity whose forecast errors the aggregator can compensate independently of the remuneration. The average hourly values for up, down and total reserves are displayed in Table 4.5 for the different configurations (with/without V2G, perfect information/driving pattern uncertainty, and the different settings of the contract). The impact of market bid uncertainty is not analyzed in this chapter.

The average hourly capacity is computed as

\[
\frac{\sum_{p=1}^{P} \sum_{d=1}^{D} \sum_{t=1}^{T} \left( C_{pdt}^{+} + C_{pdt}^{-} \right)}{PDT},
\]

(4.52)

where \( p \) is the index for the seven different wind profiles, \( d \) the index for the days of the week, and \( t \) the index for the hourly time steps.

Except for the case with driving pattern uncertainty and V2G, the largest total potential is reached for the case where constant contracted capacities apply, and the second largest potential for the unconstrained case. Without V2G, the third largest potential is obtained for symmetric capacities, and the smallest potential for symmetric and constant capacities. With V2G, the orders depend on whether there is perfect information or not. These results are again counter-intuitive: One would expect that imposing symmetric and constant capacities should lead to the smallest potential, since it is the most restrictive case. However, as discussed above, by eliminating some degrees of freedom, the deviations due to regulation requests become more predictable. Therefore, one needs to be less conservative about the uncertainty related to these requests, which enables higher capacity offers.

For the same reason, driving pattern uncertainty can have a sizable impact on the total amount of reserves that can be provided (up to 28% reduction): driving pattern uncertainty has an indirect impact here, because a larger number of samples of balancing requests need to be considered if driving pattern uncertainty is present, see §4.2.1. Note that there is a single case where the total capacity increases with driving pattern uncertainty. This happens for the case without V2G and
symmetric and constant constraints. The reason is that the expected total consumption is slightly higher under driving pattern uncertainty, which is of advantage when offering a constant of up-reserve capacity.

Enabling V2G has only a small impact in some configurations (constant capacities), and a larger impact on others. However, it does have a clear impact on the costs of providing reserves, as discussed in the following.

Note that the capacity potentials obtained here are much larger than those reported for regulation in Table 4.3. This is because reserves are defined differently in each of the cases. For regulation reserves, the full regulation capacity can be requested, see \((4.2),(4.3),(4.6),(4.7)\). However, the contract is defined in a different way here for wind forecast error balancing reserves. The contracted capacity corresponds to the wind power capacity whose forecast errors are to be balanced, but the size of the requests is a function of the day-ahead forecast. The normalized requests lie between \(1 - f_t\) and \(f_t\), see \((4.43),(4.44)\), where \(f_t\) is the normalized forecast. Therefore, unless no wind power output \((f_t = 0)\) or the highest possible output \((f_t = 1)\) are forecasted, the full contracted capacity is not requested.

**Offered capacity as a function of remuneration**

Fig. 4.12 shows the average hourly contracted capacity for the simulated week as a function of the capacity price.

In terms of total offered capacity, we observe the following order, from highest to lowest, without V2G (Fig. 4.12a): constant, no constraints, symmetric, symmetric and constant.

For lower capacity prices, we observe the following order, in terms of total offered capacity, with V2G (Fig. 4.12b): constant, closely followed by no constraints, symmetric, symmetric and constant. For higher capacity prices, we observe the order seen in Table 4.5: no constraints, symmetric, symmetric and constant, constant.
### Table 4.5: Average hourly balancing capacity potential [MW].

<table>
<thead>
<tr>
<th></th>
<th>unc(^1)</th>
<th>sym(^2)</th>
<th>cons(^3)</th>
<th>sym&amp;cons(^4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>no V2G</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(C^+)</td>
<td>pi</td>
<td>443.13</td>
<td>402.16</td>
<td>340.51</td>
</tr>
<tr>
<td></td>
<td>du</td>
<td>558.43</td>
<td>377.96</td>
<td>353.02</td>
</tr>
<tr>
<td>V2G</td>
<td>pi</td>
<td>1190.66</td>
<td>503.58</td>
<td>1198.54</td>
</tr>
<tr>
<td></td>
<td>du</td>
<td>959.10</td>
<td>467.45</td>
<td>864.20</td>
</tr>
<tr>
<td></td>
<td>no V2G</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(C^-)</td>
<td>pi</td>
<td>397.03</td>
<td>402.16</td>
<td>681.45</td>
</tr>
<tr>
<td></td>
<td>du</td>
<td>223.30</td>
<td>377.96</td>
<td>467.38</td>
</tr>
<tr>
<td>V2G</td>
<td>pi</td>
<td>0.00</td>
<td>503.58</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>du</td>
<td>70.39</td>
<td>467.45</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>no V2G</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(C^+ + C^-)</td>
<td>pi</td>
<td>840.16</td>
<td>804.33</td>
<td>1021.96</td>
</tr>
<tr>
<td></td>
<td>du</td>
<td>781.73</td>
<td>755.93</td>
<td>820.41</td>
</tr>
<tr>
<td>V2G</td>
<td>pi</td>
<td>1190.66</td>
<td>1007.16</td>
<td>1198.54</td>
</tr>
<tr>
<td></td>
<td>du</td>
<td>1029.49</td>
<td>934.91</td>
<td>864.20</td>
</tr>
</tbody>
</table>

\(^1\) unc: unconstrained, i.e. no constraints apply on the reserved capacities;  
\(^2\) sym: symmetric capacities;  
\(^3\) cons: constant capacities;  
\(^4\) sym&cons: symmetric and constant capacities;  
\(^5\) pi: perfect information;  
\(^6\) du: driving pattern uncertainty.
Figure 4.12: Average hourly offered balancing capacity as a function of the capacity price.
The tradeoff between the day-ahead charging costs and the offered capacity is illustrated in Fig. 4.13. The costs of charging are normalized with the costs obtained in the previous chapter, when providing reserves was not considered. In some cases, the charging costs are actually reduced compared with that reference (normalized costs lower than 1). In fact, a substantial capacity can be offered at no additional cost. This happens when the aggregator needs to buy less energy in total in the day-ahead market, i.e. when additional charging is obtained on average through the provision of down-reserves, see (4.37)\(^9\). Through the additional flexibility provided by V2G, the corresponding tradeoff curves tend to be lower (lower costs) and further to the right (higher capacity) than those without V2G.

The ends of the tradeoff curves represent the capacity that would be provided even if there is no capacity payment (left end), and the maximum capacity that can be offered (right end). By comparing the position of one of the ends of the curve across the curves, we recover the ranking of results discussed above.

\(^9\)Note that the energy payments have not been considered here, so the results do not take into account that the energy obtained through down-reserve requests needs to be paid for.
Figure 4.13: Tradeoff between offered balancing capacity (hourly average) and day-ahead charging costs. The charging costs are normalized by the charging costs without providing reserves. Driving pattern uncertainty is taken into account.
Finally, the impact of the shape of the wind profile on the results is analyzed in Fig. 4.14. The fourth wind profile seems to be the most favorable for the provision of balancing reserves. The least propitious profile is the sixth one. In fact, the ranking of the average offered capacities (computed with $g_t^+ = g_t^- = 10\€/MW/h$) corresponds to the inverse ranking of average daily forecasted wind output (from largest to smallest capacity, and smallest to largest forecasted wind output): 4, 5, 1, 2, 3, 7, 6. This result suggests that, the lower the forecasted wind output, the more attractive for the PEV fleet to balance the corresponding forecast error. This is because if the forecasted wind output is low, the worst-case up-reserve requests (which correspond to the forecasted value $f_t$) are not as high as if the forecasted wind output is high. Since PEVs can more easily provide down-reserves than up-reserves, their capability to offer reserves is higher when the forecasted wind output is low.
Figure 4.14: Average hourly offered balancing capacity for each of the wind profiles. The ranges are given for capacity prices between $g_t^+ = g_t^- = 0\text{€}/\text{MW}/\text{h}$ and $g_t^+ = g_t^- = 1000\text{€}/\text{MW}/\text{h}$. The displayed mean is computed across the four different capacity constraint scenarios, for the capacity price $g_t^+ = g_t^- = 10\text{€}/\text{MW}/\text{h}$. Driving pattern uncertainty is taken into account.
4.5. Case study

Typical profiles

Finally, some typical energy, charge and reserve capacity profiles are analyzed. The displayed results correspond to the capacity price $g^+_t = g^-_t = 10€/MW/h$, the first day of the simulated week and wind profile 4. Figs. 4.15 and 4.16 show the power and energy profiles, respectively, without V2G, while Figs. 4.17 and 4.18 show the profiles with V2G. The corresponding average hourly offered capacities are reported in Table 4.6.

Table 4.6: Average hourly offered balancing capacity [MW] for the first day of the simulated week and wind profile 4, assuming the capacity price $g^+_t = g^-_t = 10€/MW/h$, and perfect information.

<table>
<thead>
<tr>
<th></th>
<th>$C^+$</th>
<th>$C^-$</th>
<th>$C^+ + C^-$</th>
</tr>
</thead>
<tbody>
<tr>
<td>no V2G</td>
<td>17.05</td>
<td>1214.71</td>
<td>1231.75</td>
</tr>
<tr>
<td>V2G</td>
<td>369.26</td>
<td>1050.90</td>
<td>1420.16</td>
</tr>
<tr>
<td>sym</td>
<td>670.03</td>
<td>1025.72</td>
<td>1340.07</td>
</tr>
<tr>
<td>cons</td>
<td>499.20</td>
<td>1208.73</td>
<td>1707.93</td>
</tr>
<tr>
<td>sym&amp;cons</td>
<td>521.34</td>
<td>769.99</td>
<td>1539.98</td>
</tr>
</tbody>
</table>

1 unc: unconstrained, i.e. no constraints apply on the reserved capacities;  
2 sym: symmetric capacities; 3 cons: constant capacities; 4 sym&cons: symmetric and constant capacities.

- No V2G / no constraints

The charge profile deviates from the reference profile (no reserves) by shifting part of the load from the night to the middle of the day (Fig. 4.15a). The energy profile is shifted downwards as much as possible through $\Delta E$ (Fig. 4.16a) which allows to provide a substantial amount of down-reserves. Only a small amount of up-reserves is provided, since down-reserves are more attractive. Because more down-reserves than up-reserves are provided, the scheduled final energy content is lower than the initial energy content. The gap is expected to be bridged through the balancing requests (Fig. 4.16a).
Chapter 4. Ancillary service provision

- **No V2G / symmetric**
  The charge profile deviates from the reference profile by spreading the load more evenly (Fig. 4.15b). This leads to a flatter energy profile (Fig. 4.16b), which allows to provide symmetric reserve capacities. The energy shift $\Delta E$ is small in this case, to leave a large margin for deviations downwards (due to up-reserves). Note that although symmetric capacities are offered, the deviations in terms of power are not symmetric, since they are weighted with $f_t$ for up-reserves and $1 - f_t$ for down-reserves. Because the forecasted value is not very high, the upward deviations in terms of power (due to down-reserves) are more important. However, the deviations in terms of energy, which depend on the extracted scenarios, are more balanced, i.e. there is not a strong bias towards upward or downward deviations. For this reason, the scheduled final energy content is only slightly lower than the initial energy content. The scheduled charging demand is always at least as high as the offered up-reserve capacity times the normalized forecast, because up-reserves are provided by reducing the scheduled demand (no V2G) (Fig. 4.16b).

- **No V2G / constant**
  The charge profile deviates from the reference profile by reducing the load during the night hours, and by scheduling at least a small amount of charging power at every time step (Fig. 4.15c). The energy profile is shifted downwards through $\Delta E$ (Fig. 4.16c), which allows to provide a substantial amount of down-reserves, while some margin is left for downward deviations due to up-reserves. Only a small amount of up-reserves is provided, since down-reserves are more attractive. Because more down-reserves than up-reserves are provided, the scheduled final energy content is lower than the initial energy content (Fig. 4.16c).

- **No V2G / symmetric and constant**
  The charge profile deviates from the reference profile by spreading the load evenly throughout the day (Fig. 4.15d). This leads to a flatter energy profile (Fig. 4.16d), which allows to provide symmetric reserve capacities. The scheduled charging demand is always at least as high as the offered up-reserve capacity times the normalized forecast, because up-reserves are provided by reducing the scheduled demand (no V2G). Since the offered reserve
capacities need to be constant throughout the day, a minimum charging power is imposed at every time step. Because symmetric capacities are provided, and the energy deviations are more or less balanced, the scheduled final energy content is only slightly lower than the initial energy content (Fig. 4.16d).
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\[ P_{A,\text{min,free}} \rightarrow P_{A,\text{max,free}} \]

\[ P^A - C^+ \circ f \quad \rightarrow \quad P^A + C^- \circ (1 - f) \]

Figure 4.15: Scheduled power profile \((P^A)\) and worst case deviations when balancing the wind forecast error without V2G for the first day of the simulated week, assuming the capacity price \(g_i^+ = g_i^- = 10\€/\text{MW/h}\), and perfect information. The reference charge profile \((P^{A,\text{ref}})\) when no reserves are provided is displayed for comparison.
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Figure 4.16: Scheduled energy profile when balancing the wind forecast error without V2G ($E^A$) for the first day of the simulated week, assuming the capacity price $g_t^+ = g_t^- = 10\mathcal{E}/\text{MW/h}$, and perfect information. The worst case deviations from the scheduled energy profile are also plotted, as well as the initial energy content $E^A_{(t=0)}$. The reference energy profile ($E^A,\text{ref}$) when no reserves are provided is displayed for comparison.
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- **V2G / no constraints**
  The charge profile deviates from the reference profile by shifting part of the load from the night to the shoulder hours (Fig. 4.17a). The energy profile is shifted downwards through $\Delta E$ (Fig. 4.18a), to provide mainly down-reserves, while some margin is left for downward deviations due to up-reserves. Less up-reserves than down-reserves are provided, since down-reserves are more attractive. Because more down-reserves than up-reserves are provided, the scheduled final energy content is lower than the initial energy content (Fig. 4.18a).

- **V2G / symmetric**
  The charge profile deviates from the reference profile by shifting part of the load from the night to the shoulder hours and the end of the day (Fig. 4.17b). This leads to a slightly flatter energy profile (Fig. 4.18b), which allows to provide symmetric reserve capacities. The energy shift $\Delta E$ is zero in this case, to leave a large margin for deviations downwards (due to up-reserves). These are more important than the deviations upwards, because the downward deviations are weighted with the discharging efficiency (1/0.9 instead of 0.9). Because symmetric capacities are provided, and the energy deviations are more or less balanced, the scheduled final energy content is only slightly lower than the initial energy content (Fig. 4.18b).

- **V2G / constant**
  The charge profile deviates from the reference profile by shifting part of the load from the night to the middle of the day and the shoulder hours (Fig. 4.17c). The energy profile is shifted downwards through $\Delta E$ (Fig. 4.18c), to provide mainly down-reserves, while a sufficient margin is left for downward deviations due to up-reserves. More down-reserves than up-reserves are provided, since down-reserves are more attractive. Because more down-reserves than up-reserves are provided, the scheduled final energy content is lower than the initial energy content (Fig. 4.18c).

- **V2G / symmetric and constant**
  The charge profile deviates from the reference profile by shifting part of the load from the night to the shoulder hours (Fig. 4.17d). This leads to a flatter energy profile (Fig. 4.18d), which allows
to provide symmetric reserve capacities. The energy shift $\Delta E$ is zero in this case, to leave a large margin for deviations downwards (due to up-reserves). Because symmetric capacities are provided, and the energy deviations are more or less balanced, the scheduled final energy content is only slightly lower than the initial energy content (Fig. 4.18d).
Figure 4.17: Scheduled power profile ($P^A$) and worst case deviations when balancing the wind forecast error with V2G for the first day of the simulated week, assuming the capacity price $g^+_t = g^-_t = 10\text{\,€/MW/h}$, and perfect information. The reference charge profile ($P^{A,\text{ref}}$) when no reserves are provided is displayed for comparison.
4.5. Case study

Figure 4.18: Scheduled energy profile when balancing the wind forecast error with V2G ($E^A$) for the first day of the simulated week, assuming the capacity price $g_t^+ = g_t^- = 10\$\text{/MW\text{/h}}, and perfect information. The worst case deviations from the scheduled energy profile are also plotted, as well as the initial energy content $E^A_{\left(t=0\right)}$. The reference energy profile ($E^A_{\text{ref}}$) when no reserves are provided is displayed for comparison.
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4.5.4 Decentralized scheduling of regulation reserves

The results of the decentralized reserve scheduling described in §4.3 are compared with those of a centralized scheduling, in order to assess if the aggregated model used in the centralized approach correctly captures the flexibility available to provide reserves. As seen in §3.9, the aggregated model performs satisfactorily in the context of charging cost minimization.

The centralized approach used as benchmark is the welfare maximizing centralized scheduling\textsuperscript{10} described in §3.2, where the objective function (3.3a) has been extended to take into account the remuneration from providing regulation, i.e.

\[
\sum_{t=1}^{T} \left( \sum_d c_{dt}^D P_{dt}^D - \sum_s c_{st}^S P_{st}^S + g_t^+ C_t^+ + g_t^- C_t^- \right). \tag{4.53}
\]

The rolling horizon discussed in §3.4 is not applied to the decentralized approach here, to be able to compare the results directly.

Since the decentralized scheduling is computationally very demanding\textsuperscript{11} the analysis is only performed for the first day of the reference week (21/10/13).

Regulation capacity potential

First, the regulation capacity potentials of the centralized and decentralized reserve scheduling approaches are compared. Thereby it is possible to assess how accurately the aggregated model captures the maximum available flexibility for regulation. The average hourly values (across 24 hours) for the symmetric case without V2G are reported in Table 4.7.

\textsuperscript{10}Note that the decentralized approach is a welfare maximizing approach, and, therefore, the corresponding results cannot be directly compared with the bidding strategy described in §4.2.

\textsuperscript{11}This would not be the case in practice when the computation is performed by the PEVs in parallel: Since PEVs could solve the simple problems shown in Table 4.1 in the order of milliseconds, each stage of the problem could be solved in the order of seconds. However, in a simulation context, the parallelization is limited to the number of processor cores, 12 in this case.
The aggregated model (centralized approach) underestimates the truly available potential and therefore the available flexibility: The potential is 14%/20% lower with the aggregated model under perfect information and with driving pattern uncertainty, respectively. Driving pattern uncertainty has a lower impact on the decentralized scheme (5% reduction of the potential compared with 11% reduction). This is also possibly due to the better representation of the available flexibility in the individual model.

**Table 4.7:** Centralized vs. decentralized approaches – Average hourly regulation capacity potential [MW].

<table>
<thead>
<tr>
<th></th>
<th>perfect information</th>
<th>driving uncertainty</th>
</tr>
</thead>
<tbody>
<tr>
<td>centralized</td>
<td>231.32</td>
<td>205.07</td>
</tr>
<tr>
<td>(aggregated model)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>decentralized</td>
<td>269.00</td>
<td>255.46</td>
</tr>
<tr>
<td>(individual model)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Offered capacity as a function of remuneration**

Fig. 4.19 shows the average hourly offered capacity for the simulated day as a function of the capacity price, for both the centralized and decentralized approaches (symmetric case, no V2G). Although, the centralized scheme underestimates the available capacity, it also underestimates the costs of providing that capacity. For this reason, at lower capacity prices, the offered capacity is higher with the aggregated model.

This is seen more clearly with the tradeoff curves displayed in Fig. 4.20, showing the tradeoff between the day-ahead charging costs and the offered capacity. The tradeoff curve for the centralized case lies below that of the decentralized case most of the time, and only crosses the curve of the decentralized case when it gets close to the maximum available potential.

Since the aggregated model underestimates the total available flexibility to provide regulation reserves, it is surprising that it also underestimates the costs of providing regulation capacity. A possible explanation can be found by comparing the charge profiles without providing regulation, shown in the case study of the previous chapter (§3.9.3), in Fig. 3.20.
Compared with the curve obtained with the decentralized method, the curve obtained with the centralized method moves part of the charging from the night to the shoulder hours. Since this is also what happens when regulation is to be provided (to obtain a flatter energy curve), the additional costs of doing so in the centralized approach are lower than those in the decentralized approach.

\[ g_t^+ - g_t^- = [\text{e/MW/h}] \]

**Figure 4.19:** Centralized vs. decentralized approaches – Average hourly offered regulation capacity as a function of the capacity price for the first day of the simulated week (21/10/13). The shaded areas represent the relevant price ranges, 7.5-15 €/MW/h and 15-150 €/MW/h. Driving pattern uncertainty is taken into account.
**Figure 4.20:** Centralized vs. decentralized approaches – Tradeoff between offered regulation capacity (hourly average) and day-ahead charging costs. The charging costs are normalized by the charging costs without providing regulation. Driving pattern uncertainty is taken into account.
Typical profiles

Finally, some typical energy, charge and regulation capacity profiles are analyzed, see Fig. 4.21. The displayed results correspond to the capacity price $g_t^+ = g_t^- = 15\text{€}/\text{MW}/\text{h}$, which is at the higher end of the most common price range, and the first day of the simulated week. The corresponding total average hourly offered capacity is 242.75 MW.

The charge profile deviates from the reference profile by spreading the load more evenly, i.e. moving part of it from the night to the shoulder hours and evening (Fig. 4.21a). This leads to a flatter energy profile (Fig. 4.21b), which allows to provide symmetric regulation capacities. The scheduled charging demand is always at least as high as the offered up regulation capacity, since up regulation is provided by reducing the scheduled demand (no V2G). Because symmetric capacities are provided, the scheduled final energy content is only slightly lower than the initial energy content.
4.6 Concluding remarks

In this chapter, the charging cost minimization framework introduced in the previous chapter was extended to consider using the charging (and discharging) flexibility to provide ancillary services. The chapter focuses specifically on the provision of secondary frequency control and real-time balancing for RES forecast errors. Both a centralized and a decentralized scheduling approach were introduced.

Based on the case study using data for Switzerland, the following conclusions are in order:

Figure 4.21: Scheduled power profile and energy profiles ($P^A, E^A$), and worst case deviations when offering regulation for the first day of the simulated week, assuming the capacity price $g_t^+ = g_t^- = 15\,€/MW/h$, and perfect information. The reference charge and energy profiles ($P^A, E^A$, ref) when no regulation is provided are displayed for comparison.
• PEVs can provide a substantial amount of regulation and RES balancing reserve capacity, without increasing the costs of procuring the charging demand significantly.

• Because reserves typically need to be provided with high reliability, a scenario-based robust approach is proposed to consider the uncertainty of the regulation/balancing requests. In some cases, restraining from using all available degrees of freedom in the reserve offers (e.g. offering symmetric capacities only) can be beneficial, since the predictability of the regulation/balancing requests is increased thereby.

• The aggregated representation of the PEVs’ flexibility underestimates the available regulation capacity and the costs of offering this capacity. Therefore, in this case, it would be advisable to improve the single aggregated representation, e.g. splitting it into aggregations of clusters of vehicles with similar characteristics and driving patterns.

It was noted that the cumulative deviations from the scheduled energy profile due to ancillary service requests can be quite limiting for energy-constrained resources, such as PEVs, offering such services. In some control areas, system operators ensure that real-time regulation signals are zero mean over fixed durations (this is the case, e.g., for PJM), which significantly improves the capability of PEVs to provide regulation [29].

The case study in this chapter compared the capability to provide ancillary services with and without V2G. To establish if using V2G is a profitable strategy, one should compare the additional revenues from providing services with V2G, with the costs associated with V2G. These costs are both investment costs in V2G-ready charging infrastructure and equipment onboard the PEV, and potentially operational costs due to the accelerated battery aging.
Chapter 5

Case study for Switzerland
In this chapter, a case study performed within the project Technology-centered Electric Mobility Assessment (THELMA) is described. The institutions involved in this project are the Swiss Federal Laboratories for Materials Science and Technology (EMPA), the Paul Scherrer Institute, and research groups within ETH Zurich, namely, the Aerothermochemistry and Combustion Systems Laboratory, the Ecological Systems Design group, the Institute for Transport Planning and Systems, and the Power Systems Laboratory. The goal of the project THELMA was to understand the multi-criteria, sustainability implications of widespread electric vehicle use in Switzerland. In this chapter, the focus is on the impact of electric mobility on the power system. In particular, the influence of higher PEV penetration rates on the transmission grid, as well as on the generation mix, is analyzed. Different types of charging schemes are compared in this respect. Also, the potential contribution of PEVs to secondary frequency control (regulation) reserves is analyzed.

In contrast to the case studies presented in the previous chapters, specific scenario assumptions aiming at representing possible future mobility and energy contexts are defined here. Moreover, detailed fleet composition and PEV consumption models are considered.

Since the Swiss Federal Council and Parliament decided, in 2011, to gradually phase out nuclear power plants, a new long-term energy policy, the “Energy Policy 2050”, is being developed [9]. The electricity demand and supply scenarios considered here are related to this new energy policy. The year considered in this case study is 2035, the year by which the electricity production mix in Switzerland should be nuclear power free.

First, the model inputs are described in §5.1. Then, the models used to model charging §5.2, regulation provision §5.3, and battery degradation §5.4 are introduced. Finally, results are discussed in §5.5 and §5.6 concludes the chapter.

## 5.1 Model inputs

In the following, the model inputs describing the future Swiss power system §5.1.1 and PEV fleet §5.1.2 are described. Some of these inputs are external inputs from the THELMA project partners.
5.1. Model inputs

5.1.1 Power system

Electricity supply and demand scenarios (external input)

The supply mix and demand profiles for the year 2035 were obtained from a Swiss TIMES electricity model developed by the Paul Scherrer Institute in Switzerland [164]. TIMES is a bottom-up energy model combining the MARKAL and EFOM models. Three supply and three demand scenarios were defined for the case study [165]. The considered supply scenarios are:

- **Base**: base-case scenario.
- **Nuc**: no nuclear phaseout, i.e. investments in new nuclear power plants are allowed.
- **RES**: scenario with stronger focus on renewable energy sources (RES).

The considered demand scenarios are:

- **WWB**: business as usual (“weiter wie bisher” in German).
- **POM**: policy measures.
- **NEP**: new energy policy (most ambitious demand reduction scenario).

The future electricity demand is highest in the WWB scenario (increasing trend) and lowest in the NEP scenario (decreasing trend).

On the supply side, the total installed capacity and costs for different generation technologies, as well as typical daily generation profiles for these generation technologies in different seasons, are provided. The generation technologies considered are the following:

- **Gas**: Base / Combined Heat and Power (CHP) / Flexible (peak)
- **Nuclear**
- **Hydro**: Storage / Pumped / Run of river
RES: Geothermal / Photovoltaic / Wind / Waste / Other

On the demand side, typical daily demand profiles for the different seasons are defined, as well as daily profiles for exports/imports from/to the neighboring countries, i.e. Germany, Italy, Austria and France.

The TIMES model provides typical daily dispatch profiles for the considered generation technologies, which are computed without consideration of network constraints. Although the dispatch profiles from the TIMES model are considered as a reference here, a new dispatch accounting for transmission network constraints is performed in the case study. This dispatch is based on a DC optimal power flow (DC-OPF).

Transmission network model

The Swiss transmission system operator, Swissgrid, provided a model of the transmission network, comprising the network topology, as well as line and transformer parameters. The currently planned network extensions have been added to the present model, see Fig. 5.1. For new lines, the values assumed for the line capacity and the line reactance are based on the estimated length of the line and typical line parameters. Note that the plans in [166] only consider the time horizon up to 2015, whereas the simulation corresponds to the year 2035.

The network model comprises 272 lines (of which 37 are tie lines providing connection with neighboring countries), 20 transformers, and 199 nodes. From those nodes, 37 are in the neighboring countries, and 88 are considered load nodes, i.e. they feed an underlying medium voltage network. The loading limits of the lines are defined differently depending on the time of the year: Typically a value is given for the winter (highest), fall/spring (intermediate), and summer (lowest).

Integration of different power sources and demand into the OPF

To be able to integrate the supply and demand scenario data into the grid simulation, a pre-processing is required. An important aspect is the geographic mapping of the different technologies, so that they can be assigned to particular network nodes. For larger power plants, such
5.1. Model inputs

Figure 5.1: Current Swiss high voltage network and planned extensions up to 2015. Image from [166] (legend translated to English).

as hydro, gas, and nuclear power plants, as well as waste incinerators, the (potential) geographic position is determined. Subsequently, they are assigned to the closest network node. The list of hydro power plants in Switzerland is published in [167]. Most of the hydro power plants reported in [167] were considered. The potential future locations for gas power plants, and the location of waste incinerators were provided by the Paul Scherrer Institute. The power output of sources that play a minor role in the energy mix, such as wind, “other RES”, geothermal and gas-CHP, is directly subtracted from total demand. A more detailed approach is used to map the photovoltaic power generation to the network nodes, see below.

In the following, technology-specific modeling assumptions are described:

**Photovoltaic:** The aggregated Swiss-wide photovoltaic production profile defined in the supply and demand scenarios is assigned to individual network nodes with weights proportional to the building area of the closest municipalities multiplied with the yearly global radiation of the closest weather station [168]. The underlying assumption is that
the presence of photovoltaic panels is related to the available rooftop area, and that their actual output is related to the radiation. The building area of each municipality is used as a proxy for the rooftop area. Only the subset of network nodes that are considered load nodes is taken into account in the assignment. Photovoltaic power is included in the OPF with zero marginal costs and is considered curtailable.

**Storage and pumped hydro:** A constraint in the OPF ensures that the total daily energy production of each of these two technologies is equal to the amount defined in the supply and demand scenarios, i.e. the production of these technologies is not only power-, but also energy-constrained. The costs assigned to storage and pumped hydro in the dispatch model are not the actual production costs, but an estimation of their opportunity costs, i.e. of their water values. It is assumed that power plants with a lower energy/power ratio (peaking plants) bid higher prices, and therefore are dispatched fewer hours. Since storage and pumped hydro plants fill the gap between base gas power plants and peak gas power plants, it is assumed they bid costs in-between those values. The bid prices are scaled linearly with the historical energy/power ratio of each individual plant, as given by the statistics.

**Run of river hydro:** The total daily energy production from this technology is also set equal to the amount defined in the supply and demand scenarios. The maximum power of individual plants for a given season is set so that the total power of this type of plant is equal to the power profile given by the supply and demand scenarios. Individual power values for each plant are scaled according to the amount of energy that the plant produces during a given season, as given by the statistics. Since run of river plants can store small amounts of water, they are allowed to increase/decrease their production around the nominal value by 20% throughout the day. This is approximately the variation that can be observed in practice for run of river plants in Switzerland.

**Waste:** The maximum power of individual plants for a given season is set so that the total power of this type of plants is equal to the power profile from the supply and demand scenarios. The power of each power plant is scaled according to its CO₂ emissions, provided by the Paul Scherrer Institute.
5.1. Model inputs

**Baseload plants (nuclear, waste and gas base plants):** A constraint is set so that the power of nuclear, waste, and gas base plants is constant throughout the day.

**Exports and imports:** A constraint is set that specifies the amount of power flowing through a border with one of the neighboring countries according to the supply and demand scenarios: An inequality constraint states that imports/exports can be as high as the value given in the supply and demand scenarios, but not higher. To make sure that the import and export profiles from the OPF are as close as possible to those defined in the scenarios, imports and exports are assigned a negative cost in the cost function. Therefore, there is an incentive to import and export as much as possible within the bounds defined by the scenarios, i.e. there is a soft constraint on the amount of imports and exports.

**PEV load:** Part of the load defined in the demand scenarios corresponds to an estimate of the future PEV charging demand. Since the PEV load is modeled in detail in the THELMA project, the scenario-specific charging demand is subtracted from the total demand given in the scenarios. The PEV demand is then modeled explicitly as explained in §5.2.

5.1.2 PEV fleet

**Driving patterns (external input)**

As in the other chapters, driving patterns from the agent-based transport simulation MATSim are used here. However, this particular MATSim simulation was parameterized to represent driving patterns in the future (2030) \[65, 171\]. For this purpose, population trends and developments in the transport network were considered, see details in \[65\]. The MATSim simulations used for this case study comprise 10% of the population. Therefore, the vehicle parameters are scaled with the factor 10 so that each vehicle represents 10 vehicles in practice.

**PEV penetration and fleet composition scenarios (external input)**

Another input to the model is fleet scenarios defining which fraction of the overall fleet is expected to be electrified by a given time horizon.
Moreover, for specific agents of the transportation simulation, the vehicle class, vehicle model year and battery size is defined. Details on the underlying assumptions and models are given in [65]. The main characteristics of the model are given in the following.

In total, three different penetration scenarios are considered, each assuming a target level of 30%, 60% or 90% electrification of the fleet by 2050. However, the horizon considered in the simulation is the year 2035. The number of electric vehicles at this time horizon is 467'040, 689'690, and 716'580, in the 30%, 60% and 90% electrification scenarios, respectively. Vehicle retirements and purchases are assumed to follow an s-shaped logistic curve, see example in Fig. 5.2. The parameters of the logistic curves are different for the different considered vehicle classes: mini, small, medium, upper medium, luxury, multi-purpose vehicle (MPV), sport utility vehicle (SUV), sport, van. For each of the vehicle classes, two battery sizes are specified, a short-range variant and a normal variant. Note that, because of the s-shaped logistic curve, the number of PEVs in the 90% penetration scenario, by 2035, is not much higher than that of the 60% scenario.

![Figure 5.2: Example of s-shaped logistic curve.](image)

Once the number of PEVs in each vehicle class for a given penetration scenario are determined, these need to be allocated to specific agents from the transport simulation. One of the parameters considered in this assignment is the minimum daily driven distance that makes a PEV of a specific vehicle class economically attractive compared with a
5.1. Model inputs

combustion engine vehicle. Another criterion is the relationship between the maximum daily driving distance and the range of the PEV.

PEV energy consumption models (external input)

Based on the driven distances from the transport simulation MATSim, the energy consumption needs to be determined. For this purpose, the following inputs are used:

• The fractions of the total driven distance, as given by MATSim for each trip, that are performed on the following driving cycle types: urban, suburban and highway.

• The energy needed for propulsion per distance driven for a specific vehicle class, model year, battery size and driving cycle type (urban, highway, rural).

• The energy needed for auxiliaries per time driven for a specific vehicle class, model year, battery size and season (summer, winter, intermediate season).

With this information, for a given PEV (with a given vehicle class, model year and battery size), the energy consumption for a given trip is computed out of a) the distances on each road type multiplied with the corresponding energy per distance driven, plus b) the trip duration multiplied with the energy needed for auxiliaries per time driven.

The models used to determine the energy for propulsion and auxiliaries are described in [172].

Geographic mapping

Based on the geographic coordinates of the parking locations reported by MATSim, a mapping to particular network nodes is performed. First, the subset of network nodes that are potential load nodes is determined, based on Swissgrid’s transmission network data. Second, the vehicles are mapped to the closest network node (Voronoi partition), see Fig. 5.3.
Figure 5.3: Mapping of MATSim parking locations to load network nodes with Voronoi partition.
5.2 Charging approaches

In the following, the different charging approaches considered in the simulations are defined, which can be categorized in uncontrolled, i.e. inflexible, charging and controlled, i.e. flexible, charging. Within flexible charging, a further distinction can be made between indirectly controlled charging and directly controlled charging.

The maximum charging power is assumed to be 3.5 kW, and the state of charge (SOC) lower and upper bounds are set to 0.2 and 0.8, respectively.

5.2.1 Uncontrolled charging

In this scenario, it is assumed that vehicles start charging at the nominal charging rate (3.5 kW) as soon as they are parked, and until their batteries are full or until they depart for the next trip. Therefore, charging is inflexible and charge profiles can be directly determined out of driving patterns, as well as physical characteristics, such as the battery size and the nominal charging rate.

5.2.2 Indirectly controlled charging

A time of use (TOU) tariff is used to incentivize PEV drivers to defer their charging to low-load hours. A two-part tariff is considered, with the higher tariff from 6:00 to 22:00, as it is currently offered by Zurich’s utility, ewz. In this case, PEVs try to postpone charging as much as possible to the low-tariff period, and charge during the high-tariff period only when urgently needed. Note that the TOU tariff used here is not an optimized one, as in §3.6. The response of a PEV to this tariff can be determined using the following optimization problem, for each PEV,

\[
\begin{align*}
\text{Min.} & \quad \sum_{t=1}^{T} \text{TOU}_t P^V_{vt} \\
\text{s.t.} & \quad (2.1), (2.3), (2.4), (2.7),
\end{align*}
\]

where (2.1), (2.3), (2.4) and (2.7) are the individual PEV demand flexibility constraints introduced in §2.2.2.

\begin{align*}
(5.1a) \\
(5.1b)
\end{align*}
5.2.3 Directly controlled charging

In this case, it is assumed that a PEV aggregator directly controls PEV charging. The centralized welfare-maximizing model in \( \S 3.2 \) is used, where the aggregated nodal charging schedules are computed within an OPF. The OPF problem \( \S 3.1 \) is extended in order to take into account the special constraints related to generation technologies and to the exogenous export and import profiles, as discussed in \( \S 5.1.1 \). Driving patterns are assumed deterministic in this case study.

In the case of directly controlled charging, the result of the OPF only gives a set of aggregated charging profiles \( P^A_{nt} \), but not individual set-points. Therefore, a second step is needed to distribute the aggregated profile into individual profiles. This is done by assessing the charging urgency of each vehicle at each time step, and charging the vehicles which need charging more urgently first\(^1\). The urgency is defined as in \( \S 3.36 \). The maximum SOC value is to be reached at some time of the day.

5.3 Regulation provision

In the case of directly controlled charging, the option to provide secondary frequency control (regulation) reserves to the transmission system operator (TSO) is also considered.

5.3.1 Establishing the regulation capacity potential

To model the provision of regulation reserves, the virtual battery constraints for the case of constant and symmetric constraints, and V2G, described in \( \S 4.2.1 \) are included in the OPF. The available potential to provide regulation is established by increasing the provided capacity in 10 MW increment steps until the problem becomes infeasible.

The worst case up and down cumulative energy deviations, \( \max_k \sum_{\tau=1}^{t} e^{k}_{r} \eta^A_r \) and \( \min_k \sum_{\tau=1}^{t} e^{k}_{r} \eta^A_r \), respectively, are derived empirically from the regulation signal time series, i.e. they are not determined probabilistically as in \( \S 4.2.1 \). Driving pattern uncertainty is also not considered in this case.

\(^1\) Note that the more elaborate tracking model in \( \S 3.7 \) was not used here.
5.3.2 Computing individual responses

With the setup described above, it is possible to verify if a PEV fleet can potentially provide a certain amount of regulation. As a second step, the regulation requests need to be broken down into individual charging setpoint changes.

To provide regulation, the aggregator has to respond to a signal from the TSO which has a typical time resolution in the range of several seconds (Automatic Generation Control, AGC, signal). In an ideal setup, with unlimited communication and computational capabilities, the aggregator would be able to obtain vehicle statuses, calculate new setpoints for each vehicle and send those setpoints to the individual vehicles in real time. However, in practice, this type of approach would probably prove impractical for large fleets, due to delays in communication and data processing. For this reason, a decentralized approach is used, in which decisions to change the charging setpoint are made by the individual vehicles, see \[57, 173\]. This approach, inspired by \[174\], has the following characteristics:

- The aggregator broadcasts a signal to the vehicles which is recalculated with each new value of the AGC signal.
- Vehicles respond to this signal according to their capabilities.
- The aggregator can measure the aggregated response.
- The vehicles send information to the aggregator on a longer time scale, in the range of several minutes.

The broadcasted signal contains a probability with which vehicles should increase charging, decrease charging or discharge by a predefined power. This probability is calculated by the aggregator based on its knowledge on the number of vehicles available to perform each of the actions. When a PEV receives the signal, it verifies whether it is capable of responding without violating its constraints. If this is the case, the PEV responds to the signal only if the result of a Bernoulli trial, with probability of success equal to the broadcasted probability, is positive. The PEV maintains the new charging setpoint until the next scheduled information update takes place. The only information that a PEV needs to exchange with the aggregator is its capability to increase/decrease
charging or discharge by the predefined amount of power for the time period extending to the next scheduled information update. Although a decrease in charging and discharging are equivalent in terms of their contribution to up regulation, discharging has a negative impact on battery lifetime since it increases cycling. Therefore, charging reduction is prioritized over battery discharge whenever this is possible. Although this type of scheme does not allow to perfectly follow the regulation signal, the response is still accurate enough [57].

5.4 Battery degradation

To assess battery degradation, the model proposed in [175] is used, based on crack propagation. Battery damage is typically represented by a single parameter, denoted \( L \) in the following, running from 0, for a new battery, to 1, when no capacity is left. The end of life of a battery is usually defined as the time when the capacity of the battery is reduced to 80% of its original capacity (\( L = 0.2 \)). The factors defined in Table 5.3 are computed according to the model proposed in [175, 176] to take into account battery degradation. They are based on the SOC profiles of the PEVs, i.e. \( \text{SOC}_{vt} = \frac{E_{vt}}{C_v} \).

Table 5.1: Input parameters for battery degradation model.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average SOC</td>
<td>( \text{SOC}^{\text{avg}} = \frac{1}{T} \sum_t \text{SOC}_{vt} )</td>
</tr>
<tr>
<td>SOC deviations from average</td>
<td>( \text{SOC}^{\text{dev}} = 2\sqrt{\frac{3}{T} \sum_t (\text{SOC}_{vt} - \text{SOC}^{\text{avg}})^2} )</td>
</tr>
<tr>
<td>Effective number of cycles</td>
<td>( N_v = \sum_t \frac{</td>
</tr>
</tbody>
</table>

According to the degradation model in [175], high and low average SOC, as well as large deviations of the SOC from the average SOC, lead to accelerated aging. The effect of ambient temperature was not considered in this case study. With this simplification [176], the additional aging incurred in a cycle \( \Delta L_v \) is given by the equation

\[
\Delta L_v = \left( K^{\text{co}} N_v e^{\left( \frac{\text{SOC}^{\text{dev}} - 1}{K^{\text{ex}}} \right)} + 0.2 \frac{t_{\text{cycle}}}{t_{\text{life}}} \right) e^{\left( \frac{K^{\text{soc}} \left( \text{SOC}^{\text{avg}} - 0.5 \right)}{0.25} \right)} \left( 1 - L_v \right),
\]

where \( K^{\text{co}}, K^{\text{ex}} \), and \( K^{\text{soc}} \) are battery parameters, and \( t_{\text{cycle}} \) and \( t_{\text{life}} \) are the duration of the cycle and the battery shelf life, respectively. Aging
acceleration is defined here as the ratio between $\Delta L_v$ and $0.2 t_{cycle}^{\text{life}}$, which would be the degradation due purely to the passing of time, without using the battery, at 0.5 average SOC.

5.5 Results

5.5.1 PEV patterns

Figures 5.4 and 5.5 give an overview of key characteristics that shape the charging profiles: the number of connected vehicles, and the arrivals and departures over time, respectively. Compared with the similar figures shown in §3.9.1, these scenarios show more activity (arrivals and departures) around the middle of the day, and therefore a lower fraction of connected vehicles during that period of time. Remember that, because of the s-shaped logistic curve, the number of PEVs in the 90% penetration scenario, by 2035, is not much higher than that of the 60% scenario.
Figure 5.4: PEVs connected over time for the different penetration scenarios.
5.5. Results

Figure 5.5: Number of PEVs arriving (solid lines) and departing (dashed lines) for the different penetration scenarios.
5.5.2 PEV charging patterns

Uncontrolled charging

Figure 5.6 shows the charging profiles under uncontrolled charging. They are related to the patterns of arrivals, see Fig. 5.5. Charging takes place when vehicles arrive at work in the morning, and at home or other locations later during the day, especially in the evening, when most vehicles are connected, see Fig. 5.4. The winter load is slightly higher than the summer load, because of the increased consumption of auxiliaries due to heating demand. This, however, would be different in warmer climates, where cooling plays a more important role than heating.

![Figure 5.6: Aggregated charge profile for uncontrolled charging in winter (solid lines) and summer (dashed lines) for the different penetration scenarios.](image)

Indirectly controlled charging

Figure 5.7 shows the charging profiles when PEVs respond to the specified TOU tariff. Since the low tariff starts at 22:00, demand increases at this time, and vehicles continue charging until their batteries are full or until the high tariff period starts, at 6:00. Note that this approach induces a significantly higher peak demand as uncontrolled charging, since the PEV load loses diversity, i.e. it is concentrated during the times of low prices.
5.5. Results

![Figure 5.7: Aggregated charge profile for indirectly controlled charging in winter (solid lines) and summer (dashed lines) for the different penetration scenarios.](image)

**Directly controlled charging**

In this case, there are no predefined charging profiles, but the set of feasible charging profiles is given by the virtual battery equations (2.14)-(2.17). The upper and lower bounds on energy \( (E_A^A, t, E_A^A, t, \text{max}) \) and power \( (P_A^A, t, \text{max}, P_A^A, t, \text{min}) \) are shown in Fig. 5.8. The upper bounds are closely related to the number of vehicles connected over time, see Fig. 5.4. The lower energy bound increases during the night so that PEVs can leave in the morning with a sufficiently charged battery. There is some inflexible charging (power lower bound), mostly during daytime, due to PEVs that perform several trips with rather short parking breaks in-between during that time.
Figure 5.8: Energy and power bounds of the virtual battery under directly controlled charging.
5.5.3 Supply and demand mixes

In total, 324+36 OPF simulations were performed (4 seasons x 3 supply scenarios x 3 demand scenarios x 3 PEV penetrations x 3 charging scenarios, plus the reference cases without PEV 4x3x3x1x1). Therefore, only results for a small subset of the simulations performed are shown.

First, the results of different supply scenarios are compared. Figures 5.9 and 5.10 show the supply and demand mix for the POM demand scenario, directly controlled charging and 90% PEV penetration on a typical winter day, for the supply scenarios Base, Nuc and RES, respectively. In the Base supply scenario, an important part of the baseload is provided by gas, whereas this role is played by nuclear power in the Nuc supply scenario. In the RES supply scenario, a variety of RES, predominantly photovoltaic, replace gas and nuclear power. Also, the ratio of exports vs. imports is much lower in this scenario. In all cases, with directly controlled charging, most of the PEV load is shifted to the night hours, when demand is lower.
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Figure 5.9: Supply and demand mixes for the scenario POM-Base/directly controlled charging/90% PEV penetration/winter.
Figure 5.10: Supply and demand mixes for the scenario POM-Nuc/directly controlled charging/90% PEV penetration/winter.
Figure 5.11: Supply and demand mixes for the scenario POM-RES/directly controlled charging/90% PEV penetration/winter.
Second, the seasonal effects are analyzed, comparing a typical winter day with a typical summer day for the POM-Base scenario, directly controlled charging and 90% PEV penetration, see Figs. 5.9 and 5.12. As expected, photovoltaic production is higher in the summer than in the winter. Exports are also higher in the summer.

**Figure 5.12:** Supply and demand mixes for the scenario POM-Base/directly controlled charging/90% PEV penetration/summer.
Third, the effect of the different charging approaches is analyzed, comparing the results of directly controlled charging, uncontrolled charging and indirectly controlled charging, for the POM-Base scenario, 90% PEV penetration on a winter day, see Figs. 5.9, 5.13 and 5.14 respectively. Note that whereas in the uncontrolled and indirectly controlled charging approaches PEV demand is an exogenous input to the OPF, in the directly controlled charging approach it is an endogenous parameter. The total amount of energy provided by each type of source does not change in the different charging approaches, only the timing of hydro production. This is related to the fact that the total amount of energy provided by hydro power plants has a fixed value, and to the assumption that import and export patterns are exogenous. If imports/exports were modeled endogenously, a change in the composition of supply could be expected.
Figure 5.13: Supply and demand mixes for the scenario POM-Base/uncontrolled charging/90% PEV penetration/winter.
Figure 5.14: Supply and demand mixes for the scenario POM-Base/indirectly controlled charging/90% PEV penetration/winter.
Finally, the results of the no-PEV penetration case were compared with the different PEV penetration scenarios, to establish the marginal technologies that cover PEV demand. In the Base supply scenarios, these are primarily gas baseload or peak plants, and partly photovoltaic and waste. In the RES supply scenarios, the marginal technologies are waste and photovoltaic. In the Nuc supply scenarios, the marginal technologies are primarily, nuclear and gas baseload, and partly waste and photovoltaic. An increase in photovoltaic generation in the mix respect to the no-PEV case means that more of the photovoltaic production potential can be used, i.e. less photovoltaic power needs to be curtailed compared with the case without PEVs. In some cases, the presence of PEV charging leads to more curtailment of photovoltaic power, typically in the uncontrolled or indirectly controlled charging approaches. This can be due to internal congestions created by the exogenous PEV demand.

Fig. 5.15 shows a comparison of the supply mix with and without PEVs for the scenario POM-Base in winter. The profiles that change are those corresponding to the different hydro power plants (run of river, storage, pumped) and to gas baseload power plants. However, the total daily production of hydro power plants is fixed, see \( \text{5.1.1} \). Therefore, the marginal power plants that cover PEV demand, in this case, are gas baseload power plants.

### 5.5.4 Asset loading and requirements for network expansion

From the OPF, it is possible to assess if the available network infrastructure is sufficient to cover the needs of generators and consumers. If the OPF problem is infeasible, and becomes feasible when line/transformer constraints are relaxed, then additional investments in the network are required. The OPF tool is however not an investment planning tool, and cannot be used to determine the optimal investment in network infrastructure. In all simulated scenarios, a feasible solution was found, implying that the introduction of PEVs should, in principle, not pose a problem for the transmission network. Note, however, that no security constraints were considered in the OPF, and if included that could change this conclusions.

The increase in average asset (lines and transformers) loading is minor,
Figure 5.15: Supply mixes for the scenario POM-Base/winter with (90\% penetration, directly controlled charging) and without PEV demand.

around 0.01\% additional loading, for all of the PEV penetration scenarios, compared with the no-PEV penetration case. This is because PEV demand has only a minor influence in the flow patterns in the transmission network.
5.5.5 Regulation capacity potential

Since this potential depends primarily on the charging flexibility, and not on the demand and supply scenarios, this analysis is performed for the POM-Base scenario only. Results are reported in Table 5.2. Given that the currently required capacity for secondary frequency control is about 400 MW, a substantial portion of this service could potentially be provided by PEV fleets. The reported capacities correspond to approximately 0.4 kW per vehicle, i.e. around 10% of the nominal power of the PEV. In some of the penetration scenarios, the potential is slightly higher in the summer, where PEV demand is lower because of the lower consumption of auxiliaries. This can be interpreted as demand being more flexible in the summer.

Table 5.2: Regulation capacity potential.

<table>
<thead>
<tr>
<th>PEV penetration scenario</th>
<th>Winter</th>
<th>Summer</th>
</tr>
</thead>
<tbody>
<tr>
<td>30%</td>
<td>190 MW</td>
<td>200 MW</td>
</tr>
<tr>
<td>60%</td>
<td>260 MW</td>
<td>260 MW</td>
</tr>
<tr>
<td>90%</td>
<td>280 MW</td>
<td>290 MW</td>
</tr>
</tbody>
</table>

5.5.6 Battery degradation

As explained in §2.3.2 when no reserves are provided by the fleet, it is assumed that the maximum SOC, set to 0.8 here, is reached at some point. To be able to provide symmetric reserves, the aggregator will typically schedule a lower average SOC. Moreover, to respond to the frequency regulation requests (AGC signal) by the TSO, the SOC dispatched in real time will deviate from the scheduled SOC. These different average SOCs for the fleet are shown in Fig. 5.16. The SOC profiles when responding to the AGC signal were computed for 7 samples of daily AGC signals (one week). Deviations from the scheduled profile are minimal for these samples.

Table 5.3 shows the aging acceleration for the different cases. The total amount of provided reserves corresponds to the values reported in Table 5.2 for each of PEV penetration scenarios. Contrary to what would be expected, providing reserves leads to lower battery degradation, at least
Chapter 5. Case study for Switzerland

according to the used battery degradation model [175]. This is because
the average scheduled SOC to provide reserves is closer to 0.5, whereas
without providing reserves, the SOC is kept high by assumption. This
assumption was adopted because a high SOC is more convenient for
users, since it lowers the risk of having an insufficiently charged battery
when spontaneously deciding to drive. If battery degradation were the
major priority, then battery degradation could be reduced by a different
charging optimization policy. The effect of degradation when respond-
ing to the AGC signal, compared with the aging with the reference
SOC scheduled when planning reserves, is not visible, at least for the 7
samples analyzed. For some days with more extreme AGC requests the
impact would be larger, but most of the times the energy requests are
modest, see Fig. 4.2.

![Figure 5.16: Average SOC of the PEVs in the fleet.](image)

5.6 Concluding remarks

The results analyzed in this chapter suggest that, under the conditions
assumed in the demand, supply and PEV penetration scenarios, PEVs
could be integrated into power systems without any major impact on the
electricity supply side, as well as the transmission network. Moreover,
PEV charging is a very flexible load that can be shaped to reduce the
costs of generation, to avoid congestions, and even to provide network
ancillary services.
5.6. Concluding remarks

Table 5.3: Battery aging acceleration.

<table>
<thead>
<tr>
<th>season</th>
<th>PEV penetration</th>
<th>reaching max SOC</th>
<th>planning reserves</th>
<th>responding to AGC</th>
</tr>
</thead>
<tbody>
<tr>
<td>winter</td>
<td>30%</td>
<td>2.2</td>
<td>1.6</td>
<td>1.6</td>
</tr>
<tr>
<td></td>
<td>60%</td>
<td>2.2</td>
<td>1.6</td>
<td>1.6</td>
</tr>
<tr>
<td></td>
<td>90%</td>
<td>2.2</td>
<td>1.7</td>
<td>1.7</td>
</tr>
<tr>
<td>summer</td>
<td>30%</td>
<td>2.1</td>
<td>1.5</td>
<td>1.5</td>
</tr>
<tr>
<td></td>
<td>60%</td>
<td>2.1</td>
<td>1.6</td>
<td>1.6</td>
</tr>
<tr>
<td></td>
<td>90%</td>
<td>2.2</td>
<td>1.6</td>
<td>1.6</td>
</tr>
</tbody>
</table>

A further analysis of the impact of PEV charging on the medium voltage distribution network of the Canton of Bern (BKW utility), not included here, but included in the final project report [65], showed that PEVs could also be integrated in the distribution grid without major problems. However, these results depend heavily on the initial loading situation of the distribution network under study.

As future work, it would be interesting to model imports and exports as endogenous parameters within the model, e.g. by assuming electricity prices for the neighboring countries. Moreover, it would be interesting to study battery degradation in more detail.
Chapter 6

Conclusion and outlook
Chapter 6. Conclusion and outlook

This chapter summarizes the content of the thesis (§6.1), draws conclusion based on the presented methods and results (§6.2), and provides suggestions for future work (§6.3).

6.1 Summary

In the background of an increasing need for flexibility in power systems, due to a growing penetration of intermittent Renewable Energy Sources (RES), and with the prospect of a more extensive use of information and communication technologies in distribution grids, it was argued that PEV charging (and discharging) flexibility could be a valuable asset. This thesis has focused on models of PEV demand flexibility, as well as on methods to generate value from this flexibility, by reducing the costs of procuring the charging demand, and by providing ancillary services.

First, in §2 individual and aggregated models of PEV charging flexibility, based on driving patterns from a transport simulation, were introduced. Specifically, flexibility is represented as a set of linear power and energy constraints, which can be used in different optimization problems. For the aggregated representation (virtual battery), a scenario-based robust approach to address driving pattern uncertainty was described.

Second, in §3 different approaches to minimize the costs of procuring the charging demand were presented, categorized along three dimensions: centralized/decentralized control, unidirectional/bidirectional communication, strategic/cooperative decision-making. Mainly, the following methods were introduced:

- A bidding strategy for a PEV aggregator, based on complementarity modeling (centralized, bidirectional, strategic).

- A bidding strategy for individual PEVs in a market-based control context, based on reinforcement learning (decentralized, bidirectional, strategic).

- A cooperative decentralized scheduling approach, based on the Alternating Direction Method of Multipliers (ADMM) (decentralized, bidirectional, cooperative).
6.2 Conclusion

- A method to determine optimal Time of Use (TOU) tariffs in a framework where PEVs respond optimally to exogenous price signals (decentralized, unidirectional).

- A hierarchical control approach combining the aggregator’s bidding strategy, and the cooperative decentralized scheduling.

Third, in §4 the aggregator’s bidding strategy and the cooperative decentralized scheduling introduced in §3 were extended to use the PEVs’ flexibility to provide regulation (or balancing services), in addition to minimizing the charging costs. Both unidirectional and bidirectional (Vehicle to Grid, V2G) charging were considered in this context, as well as different settings of the service contracts.

Finally, in §5 a case study on the impact of increasing PEV penetrations on the Swiss power system was presented, for different possible future demand, supply and PEV penetration scenarios.

6.2 Conclusion

In the following, the conclusions drawn from the analysis of the proposed methods in case studies with Swiss data are recapitulated:

- A PEV aggregator can theoretically exercise market power, but in practice this requires a very good knowledge of the other market participants’ bids. In this context, it is crucial to develop appropriate models to estimate the supply and demand curves in the power market.

- For large fleets, driving pattern uncertainty has a negligible impact on the costs of charging for the centralized and/or cooperative approaches, since a) aggregated fleet characteristics can be quite accurately forecasted (centralized approaches), and b) the aggregated schedule is robust against differences in individual schedules across scenarios when the scheduling process is coordinated (welfare maximizing decentralized approach).

- Using reinforcement learning as a strategy for decentralized charging scheduling leads to results that are close to optimal. It remains to be explored how this performance would degrade with a higher volatility of market prices and/or driving patterns.
Chapter 6. Conclusion and outlook

- Using TOU tariffs to shape PEV charging demand could be appropriate at low PEV penetrations, but, since this strategy leads to a high concentration of charging during certain hours, it is problematic at high PEV penetrations.

- The proposed virtual battery model seems to capture the available flexibility of the fleet accurately enough for large fleets, i.e. it only slightly underestimates the available flexibility and leads to an aggregated profile that can be sufficiently accurately tracked by individual PEVs.

- In any case, the gains from exploiting charging flexibility are substantial, compared with an uncontrolled charging scenario.

- PEVs can provide a substantial amount of regulation and RES balancing reserve capacity, without increasing the costs of procuring the charging demand significantly.

- Because reserves typically need to be provided with high reliability, a scenario-based robust approach is proposed to consider the uncertainty of the regulation/balancing requests. In some cases, restraining from using all available degrees of freedom in the reserve offers (e.g. offering symmetric capacities only) can be beneficial, since the predictability of the regulation/balancing requests is increased thereby.

- The aggregated representation of the PEVs’ flexibility underestimates the available regulation capacity and the costs of offering this capacity.

6.3 Outlook

There are different possibilities to extend the types of models described in this thesis, i.e. models to a) represent the flexibility of individual PEVs and PEV aggregations, and b) to schedule charging (and discharging) optimally using the available flexibility in order to generate value through interactions with other actors in the electricity sector.
Demand flexibility models

Regarding flexibility models, it would be interesting to analyze if charging scheduling approaches have an impact on driving patterns. Here, driving patterns were assumed exogenous inputs, but it could be thinkable that drivers change their driving and parking behavior if strong monetary incentives are used to shape their charging in a particular way [177], or if the charging scheduling approaches fail to satisfy their mobility needs.

Moreover, with real statistics of PEV driving patterns, models to generate such patterns could be improved to represent PEV-specific driving behavior, and the uncertainty related to individual PEV driving patterns. Machine learning tools could be used for an adaptive estimation of driving patterns.

Further, other sources of uncertainty [56] that affect the available flexibility of the PEV fleet could be considered. Such sources of uncertainty could be errors in the communication channel, or the spontaneous overriding of charging setpoints by the PEV drivers.

Finally, the accuracy of the virtual battery model presented in this thesis could be improved by representing the flexibility of clusters of similar vehicles separately.

Charging scheduling methods

Regarding the models to optimally use the charging/discharging flexibility, grid integration aspects were not treated in detail in this thesis. By coordinating charging for economic purposes (service provision, minimization of procurement costs), part of the diversity of the PEV load is lost, which could lead to problems in the network (in the distribution network mainly). In general, charging cost minimization approaches should shift demand from high-load periods to low-load periods, which is, in principle, beneficial from a network perspective. If the impact of demand on prices is taken into account in these schemes (which is not the case for TOU tariffs), then it is possible to avoid creating new demand peaks during low-load hours. However, prices reflect the overall supply and demand situation at a national or regional level, potentially reflecting congestions in the transmission network (zonal prices, locational
marginal prices), but they do not fully reflect the local loading situation at the distribution grid level [18]. This misalignment issue becomes even more complex with the increasing penetration of RES in the distribution system. When providing system-wide ancillary services (e.g. frequency control) with distributed resources, the system’s signals could also be in contradiction with local needs (e.g. when down-reserves are activated during local peak demand times) [43, 178]. Therefore, multi-level hierarchical approaches would be necessary to address the constraints that can arise at different network levels. In this thesis, a two-level hierarchical approach was presented, with a) a centralized approach in the upper hierarchy level representing the PEV aggregator taking decisions on aggregated schedules, and b) a decentralized approach for the individual scheduling of PEVs according to the aggregated schedule. The decentralized scheduling approaches presented in this thesis (market-based control, ADMM) could be extended to include multiple intermediate aggregation levels between the upper centralized level and the lower individual scheduling level, see [108, 121]. At each of the intermediate aggregation levels, the corresponding network constraints could be addressed. However, a major challenge lies in representing the impact of the limitations introduced by the intermediate aggregation levels on the highest aggregated flexibility representation (upper hierarchy level). At this level, the aggregator should make decisions on how much energy to procure and how much capacity to commit for a given ancillary service. The constraints of the intermediate aggregation levels not only make the estimation of the available flexibility more complex, but add a further source of uncertainty in this estimation.

Another possible source of conflicting interests arises when the actions of the aggregator generate costs for individual PEVs. These costs would typically come from additional battery degradation, specially if V2G is used. Individual PEV costs could be introduced in the ADMM approach in the local problems solved by PEVs (with a convex representation of battery degradation), and in the market-based control approach through appropriate modification of the market bids. However, as with the local constraints, these additional goals make the decision-making of the aggregator more complex.
Bibliography


electric vehicle charging control,” in *IEEE 52nd Annual Conference on Decision and Control (CDC)*, 2013, pp. 6960–6965.


Appendices
Appendix A

Priced-based control
MILP problem
Appendix A. Priced-based control MILP problem

In the following, the reformulation of the bilevel problem used to determine the optimal Time of Use (TOU) tariff, (3.44)-(3.46), as a Mixed-Integer Linear Programming (MILP) problem is described.

The lower level problem (3.46) of the bilevel problem can be recast as the following problem

\[
\begin{align*}
\text{Min.} & \quad \Phi_{\text{LLPC}} \sum_{t=1}^{T} \text{TOU}_t P_A^t \\
\text{s.t.} & \quad E_{t=0}^A \leq E_{t=0}^A + \sum_{\tau=1}^{T} (P_\tau^A \eta_\tau^A \Delta t + E_{t=0}^{\text{ad}}) : \mu_{t\text{min}}^E, \forall t, \quad (A.1b) \\
& \quad E_{t=0}^A + \sum_{\tau=1}^{T} (P_\tau^A \eta_\tau^A \Delta t + E_{t=0}^{\text{ad}}) \leq E_{t=0}^A : \mu_{t\text{max}}^E, \forall t, \quad (A.1c) \\
& \quad P_{t\text{min}}^A \leq P_t^A \leq P_{t\text{max}}^A : \mu_{t\text{min}}^P, \mu_{t\text{max}}^P, \forall t, \quad (A.1d) \\
& \quad \sum_{t=1}^{T} (P_t^A \eta_t^A \Delta t + E_{t=0}^{\text{ad}}) = 0 : \lambda E, \quad (A.1e)
\end{align*}
\]

with decision variables

\[
\Phi_{\text{LLPC}} = \{ P_t^A, \forall t; E_{t=0}^A \}. \quad (A.2)
\]

The term \( E_{t=0}^{\text{ad}} \) stands for the net energy contribution of PEV arrivals and departures, i.e. \( E_{t=0}^{\text{arr}} - E_{t=0}^{\text{dep}} \). The Lagrange multipliers of the constraints

\[
\Phi_{\text{dual}} = \{ \{ \mu_{t\text{min}}^E, \mu_{t\text{max}}^E, \mu_{t\text{min}}^P, \mu_{t\text{max}}^P \} : \forall t, \lambda E \}
\]

are defined after the colon.

The goal is to replace the lower level problem, which is linear, by its Karush-Kuhn-Tucker (KKT) conditions, i.e. by the stationarity conditions

\[
\text{TOU}_t + \sum_{\tau=t}^{T} \left( \left( \mu_{\tau\text{max}}^E - \mu_{\tau\text{min}}^E \right) \eta_{\tau}^A \Delta t \right) + \mu_{\tau\text{max}}^P - \mu_{\tau\text{min}}^P + \lambda E \eta_{\tau}^A \Delta t = 0, \quad (A.3)
\]

for all \( t \), and the complementarity slackness conditions

\[
0 \leq -E_{t=0}^A + E_{t=0}^A + \sum_{\tau=1}^{T} (P_\tau^A \eta_\tau^A \Delta t + E_{t=0}^{\text{ad}}) \perp \mu_{t\text{min}}^E \geq 0, \quad \forall t, \quad (A.4)
\]
\[0 \leq +E_{(t=0)}^{t,A,\text{max}} - E_t^A - \sum_{\tau=1}^{t} (P_{\tau}^A \eta_{\tau}^A \Delta t + E_{\tau}^A, \text{ad}) \perp \mu_t^{E,\text{max}} \geq 0, \quad \forall t,\]  
(A.5)

\[0 \leq -P_{t,A,\text{min}} + P_{t}^A \perp \mu_t^{P,\text{min}} \geq 0, \quad \forall t,\]  
(A.6)

\[0 \leq +P_{t,A,\text{max}} - P_{t}^A \perp \mu_t^{P,\text{max}} \geq 0, \quad \forall t,\]  
(A.7)

and the equality constraint (A.1e).

The next step is to reformulate the complementarity slackness conditions as linear constraints with the help of integer variables, denoted \(\gamma\), and large enough constants, denoted \(M\).

\[0 \leq -E_{t,A,\text{min}}^t + E_{(t=0)}^A + \sum_{\tau=1}^{t} (P_{\tau}^A \eta_{\tau}^A \Delta t + E_{\tau}^A, \text{ad}) \leq \gamma_t^{E,\text{min}} M^{E,\text{min}}, \quad \forall t,\]  
(A.8)

\[0 \leq \mu_t^{E,\text{min}} \leq (1 - \gamma_t^{E,\text{min}}) M^\mu, \quad \forall t,\]  
(A.9)

\[0 \leq +E_{t,A,\text{max}} - E_{(t=0)}^A - \sum_{\tau=1}^{t} (P_{\tau}^A \eta_{\tau}^A \Delta t + E_{\tau}^A, \text{ad}) \leq \gamma_t^{E,\text{max}} M^{E,\text{max}}, \quad \forall t,\]  
(A.10)

\[0 \leq \mu_t^{E,\text{max}} \leq (1 - \gamma_t^{E,\text{max}}) M^\mu, \quad \forall t,\]  
(A.11)

\[0 \leq +P_{t,A,\text{max}} - P_{t}^A \leq \gamma_t^{P,\text{max}} M^{P,\text{max}}, \quad \forall t,\]  
(A.12)

\[0 \leq \mu_t^{P,\text{max}} \leq (1 - \gamma_t^{P,\text{max}}) M^\mu, \quad \forall t,\]  
(A.13)

\[0 \leq -P_{t,A,\text{min}} + P_{t}^A \leq \gamma_t^{P,\text{min}} M^{P,\text{min}}, \quad \forall t,\]  
(A.14)

\[0 \leq \mu_t^{P,\text{min}} \leq (1 - \gamma_t^{P,\text{min}}) M^\mu, \quad \forall t.\]  
(A.15)

These constraints introduce the auxiliary integer variables

\[\Phi_{\text{aux}} = \{\gamma_t^{E,\text{min}}, \gamma_t^{E,\text{max}}, \gamma_t^{P,\text{min}}, \gamma_t^{P,\text{max}}\} \forall t\}.

Therefore, bilevel problem (3.44), (3.46) can be recast as the following
Appendix A. Priced-based control MILP problem

MILP problem

\[
\max_{\Phi_{ULPC}, \Phi_{LLPC}, \Phi_{dual}, \Phi_{aux}} \sum_{t=1}^{T} \left( \sum_d c_d^D P_d^D - \sum_s c_s^S P_s^S \right) \quad (A.16a)
\]

s.t.

\[
\sum_d P_d^D + P_t^A = \sum_s P_s^S, \quad \forall t, \quad (A.16b)
\]

\[
0 \leq P_d^D \leq P_d^{D,\text{max}}, \quad \forall t, \forall d, \quad (A.16c)
\]

\[
0 \leq P_s^S \leq P_s^{S,\text{max}}, \quad \forall t, \forall s, \quad (A.16d)
\]

\[
\text{[A.3]} \forall t, \quad [A.1e], \quad [A.8]-[A.15], \quad (A.16e)
\]

\[
\Phi_{aux} \in \{0, 1\}. \quad (A.16f)
\]
Curriculum Vitae

June 2003
Highschool diploma at Deutsche Schule Valencia, Spain

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Studies of Electrical Engineering and Information Technologies, French-German double degree at TU München, Germany, and Supélec, France

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