Agent-based modeling and simulation of large scale electric mobility in power systems

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presented by
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Preface

This thesis was written during my time as a researcher and assistant at the Power Systems Laboratory of the ETH Zurich from June 2007 to March 2012.

It has been a long way up to this point where the work is done, the results are generated and the document is finally written. These years of PhD studies and research account for many life changing experiences and there are only few that I would like to miss. As on every long journey there are ups and downs, comparable to a sailing trip where the boat faces bright, sunny, calm days and furious thunderstorms almost leading to a dismasting. It is the people you meet during both periods that help you reach the safe harbor, enriching your life, your experiences, your personality and, finally, also the thesis itself. This is the opportunity to thank them.

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Wehe! Es kommt die Zeit, wo der Mensch nicht mehr den Pfeil seiner Sehnsucht über den Menschen hinaus wirft, und die Sehne seines Bogens verlernt hat, zu schwirren! Ich sage euch: man muss noch Chaos in sich haben, um einen tanzenden Stern gebären zu können.

Ich sage euch: ihr habt noch Chaos in euch.

Friedrich Nietzsche, Also Sprach Zarathustra, 1883–1885.
Abstract

Due to a paradigm shift towards more sustainable socio-ecological energy systems, more and more distributed energy resources are integrated into power systems. This, together with the liberalization of electric power systems, creates numerous challenges. Build and expanded during the last century, the power system was initially not designed to cope with large amounts of distributed energy resources, sometimes far away from load centers and with fluctuating power infeed. An increased level of transnational electricity trading, one face of the liberalization, leads to an increasing number of congestion of cross-border electricity lines. Recently, in order to transform the system into one that can stand up better to these challenges, the concept of Smart Grid gained momentum. While its exact definition is still to be formulated, among other goals, the introduction and integration of large scale electric mobility is one central issue.

The benefits of individual electric transportation feature an increased overall energy efficiency, especially if the vehicles are charged by renewable energy sources, and the possibility utilize the vehicles as a potential storage in power systems. However, the introduction of individual electric mobility on a large scale also poses numerous challenges to the power system infrastructure initially not designed to supply loads of unknown temporal and, even worse, spatial behavior. The vision of using the vehicles as a storage, which includes feeding power from the vehicles to the power system, commonly referred to as vehicle-to-grid (V2G) services, aggravates the complexity of the challenge.

This thesis develops an agent based analysis tool in order to investigate the impacts of large scale electric vehicle adoption on power systems. The tool, beyond simple analysis measures, provides an agent based, intelligent charging control approach. It allows to operate the power
system infrastructure close to its feasible capacity bounds while managing the demand of large numbers of vehicles. Uniquely, the tool integrates three major domains affected by electric mobility. The domains include individual vehicle modeling, modeling of individual transportation behavior as well as modeling of power systems. Detailed energy consumption models for each individual vehicle and a fleet evolution simulation are used as inputs to a large scale, agent based transportation simulation model. The output of the transportation simulation is used as input to the charging control scheme in the power system simulation. The scheme takes advantage of the vehicles charging flexibility while supplying their energy demand. Additionally, it is also able to analyze and simulate the aggregation of the vehicles into a virtual storage and its temporal and spatial effects on power systems.

To this end, the control approach uses a distributed, predictive and hierarchical architecture, integrating different charging modes such as uncontrolled and controlled charging as well as V2G services. The thesis contributes on the discussion of how such intelligent control approaches, notably the chosen one, can be integrated into current power system legal and operational frameworks. Finally, the thesis provides a proof of concept on how electric mobility can be advantageously integrated into power systems, illustrating how, based on today’s power system structure, one pillar of the smart grid can become reality.

Kurzfassung

der Gerätschaften als Speicher erhöht zusätzlich die sowieso schon außer-
odentlich hohe Komplexität der zu lösenden Herausforderungen.

Die vorliegende Arbeit stellt sich den erwähnten, mannigfaltigen Heraus-
forderungen und entwickelt ein agentenbasiertes Analysewerkzeug zur
Untersuchung der potentiellen Auswirkungen von Elektromobilität auf
das elektrische Energiversorgungssystem, wobei insbesondere Augenmerk
auf die Belastung der derzeitig in Betrieb stehenden Infrastruktur gelegt
wird. Das Werkzeug beschränkt sich allerdings nicht auf die detaillierte
Analyse der auftreten Effekte. Die vorliegende Arbeit entwickelt eine
intelligente, ebenfalls agentenbasierte Ladesteuerung, die es erlaubt, die
vorhandene elektrische Infrastruktur effizient, bis an die Kapazitätsgren-
zen zu nutzen. Die Steuerung der Elektromobile erfolgt individuell, d.h.
jedes einzelne Vehikel wird mit seinen spezifischen Randbedingungen
berücksichtigt.

Das Werkzeug vereinigt drei der zentralsten Bereiche der Elektromo-
bilität. Diese beinhalten die einzelnen Fahrzeugeotechnologien, das ei-
gentliche Transportverhalten und das elektrische Energieversorgungssy-
stem. Das Simulationswerkzeug integriert und verwendet daher Modelle
der einzelnen, in der gesamten Verkehrsflotte vorhandenen Fahrzeug-
typen, ein Modell, das das Transportverhalten detailliert wiedergibt,
sowie ein detailliertes, realistisches Modell eines Stromversorgungssy-
tems, auf bisher einzigartige Weise, welche erlaubt Synergien zu nutzen
und detaillierte Aussagen zu treffen. Energieverbrauchsmodelle für jedes
einzelne Fahrzeug sowie eine Flottensimulation werden als Eingangs-
datensatz für die Transportsimulation verwendet. Diese liefert zeitliche
und räumliche Informationen bezüglich des Ladeverhaltens, welche als
Eingangsdaten zur Netzsimulation verwendet werden. Die Ladesteuerung
nutzt die zeitliche Ladeflexibilität und ermöglicht, Teile der Flotte zu
aggregieren und als steuerbaren, virtuellen Speicher zu nutzen.

Zu diesem Zweck nutzt die Ladesteuerung eine verteilte, prädiktive und
hierarchische Steuerungsarchitektur, die es ermöglicht die Aufladung
sowie V2G Dienstleistungen integriert zu betrachten und zu kontrol-
lieren. Die vorliegende Arbeit trägt über die vorgeschlagenen, tech-
nischen Lösungskonzepte hinaus auch zur Eruierung, wie intelligente
Steuerungsstrukturen in die aktuellen Planungs und Betriebsführungskonzepte integriert werden können, bei. Die Arbeit zeigt daher nicht nur
auf wie Elektromobilität effizient in die bestehende elektrische Infra-
struktur integriert werden kann, sondern vermittelt auch Hinweise, wie
Smart Grids Realität werden können.
## List of Acronyms

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<tr>
<th>Acronym</th>
<th>Description</th>
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<tbody>
<tr>
<td>ABM</td>
<td>Agent Based Modeling</td>
</tr>
<tr>
<td>AGC</td>
<td>Automatic Generation Control</td>
</tr>
<tr>
<td>ASP</td>
<td>Ancillary Service Provider</td>
</tr>
<tr>
<td>BG</td>
<td>Balance Group</td>
</tr>
<tr>
<td>BGM</td>
<td>Balance Group Manager</td>
</tr>
<tr>
<td>BGR</td>
<td>Balance Group Responsible</td>
</tr>
<tr>
<td>CHP</td>
<td>Combined Heat and Power</td>
</tr>
<tr>
<td>COSMO</td>
<td>Consortium for Small-Scale Modeling</td>
</tr>
<tr>
<td>DG</td>
<td>Distributed Generation</td>
</tr>
<tr>
<td>DisCo</td>
<td>Distribution System Company</td>
</tr>
<tr>
<td>EC</td>
<td>End Consumer</td>
</tr>
<tr>
<td>ENTSO-E</td>
<td>European Network of Transmission System Operators for Electricity</td>
</tr>
<tr>
<td>ESP</td>
<td>Energy Service Provider</td>
</tr>
<tr>
<td>EV</td>
<td>Electric Vehicle</td>
</tr>
<tr>
<td>Acronym</td>
<td>Description</td>
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<td>----------------------------------</td>
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<tr>
<td>GenCo</td>
<td>Generation Company</td>
</tr>
<tr>
<td>ICT</td>
<td>Information and Communication Technology</td>
</tr>
<tr>
<td>ICE</td>
<td>Internal Combustion Engine</td>
</tr>
<tr>
<td>ID</td>
<td>Identification</td>
</tr>
<tr>
<td>ISO</td>
<td>Independent System Operator</td>
</tr>
<tr>
<td>LC</td>
<td>Load Curve</td>
</tr>
<tr>
<td>MATSim</td>
<td>Multi Agent Transportation Simulation</td>
</tr>
<tr>
<td>MIMO</td>
<td>Multi-Input-Multi-Output</td>
</tr>
<tr>
<td>MPC</td>
<td>Model Predictive Control</td>
</tr>
<tr>
<td>OPF</td>
<td>Optimal Power Flow</td>
</tr>
<tr>
<td>PEV</td>
<td>Plug-In Electric Vehicle</td>
</tr>
<tr>
<td>PHEV</td>
<td>Plug-In Hybrid Electric Vehicle</td>
</tr>
<tr>
<td>PMPSS</td>
<td>PEV Management and Power System Simulation</td>
</tr>
<tr>
<td>RES</td>
<td>Renewable Energy Sources</td>
</tr>
<tr>
<td>RTB</td>
<td>Real Time Balancig</td>
</tr>
<tr>
<td>SM</td>
<td>Smart Meter</td>
</tr>
<tr>
<td>SOC</td>
<td>State of Charge</td>
</tr>
<tr>
<td>TSO</td>
<td>Transmission System Operator</td>
</tr>
<tr>
<td>V2G</td>
<td>Vehicle to Grid</td>
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<tr>
<td>VTAM</td>
<td>Vehicle Technology Assessment Model</td>
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Chapter 1

Introduction

1.1 Background and Motivation

After a period during which gasoline dominated the individual transportation sector, interest has shifted towards electric mobility. The shift is due to various factors related to current and future developments in the society. Studies have shown that the oil production might soon reach or actually has reached a peak after which the produced amount will decrease [1, 2]. Therefore, this primary energy carrier will likely become scarce in the future. As individual transportation today relies heavily on oil products, such as gasoline, finding a substitute is of great value. To this end, electricity appears to be one attractive solution [3, 4].

The strive for a sustainable society, which is able to avoid CO$_2$ emissions and hence global warming, is another reason for the growing interest in electric vehicles. One important pillar when building such a sustainable society is to increase efficiency. The individual transportation sector is a good option to work on. There, an efficiency increase can be achieved by utilizing electric vehicles [5–8].

The vehicles offer the possibility to be refueled, i.e., charged, through completely emission free sources. Renewable energy sources (RES) can be used to provide the energy to charge a large number of electric vehicles. In fact, the utilization of electric vehicles and RES offers many synergies which can be exploited [9–12].
Large scale adoption of electric vehicles will strongly affect the power system of today which already faces numerous challenges. After the liberalization of electricity markets, planning and operation of the power system have changed dramatically. New market players such as generation companies (GenCos), transmission system operators (TSOs), distribution system companies (DisCos), balance group managers (BGMs) and regulators were introduced. Based on defined market rules, they interact closely in order to balance generation and demand at all times and to keep the power system in a secure state. Besides them, traders are buying and selling electricity throughout Europe using the installed power lines, which were not originally designed and aimed for such conditions. Congestions on power lines frequently occur and are resolved through market rules [13–16].

Moreover, the portfolio of generation assets, which was heavily relying on fossil fuels, is changing towards power generation from RES, which are of fluctuating nature and are challenging to incorporate in current operation guidelines as well as in market rules [17–19]. As the electricity network was not designed for the infeed of such fluctuating sources, challenges arise in the operation of the system [20–22]. The situation calls for more storage opportunities which can store excessive energy, produced from RES during times when the load is low, and feed it back when the load is high and the RES generation is low [11, 12].

To this end, electric vehicles (EVs) and Plug-In Hybrid Electric Vehicles (PHEVs), commonly referred to in the remainder of this thesis as Plug-In Electric Vehicles (PEVs), are envisioned to act as a storage option once they sufficiently penetrated the market. They could be clustered into a virtual battery which is charged by RES and discharged if it is demanded. Such operation is referred to as vehicle to grid (V2G) operation. The aggregation and the control of the storage are envisioned to be performed by a new market player referred to as the aggregator. This new entity obviously needs to be integrated into the current power system planning and operation framework [15, 23–26].

Clearly, the issue of electric mobility has many implications on the way how power systems are operated. This dissertation investigates main aspects when integrating electric mobility into the power system. The aspects include the derivation of an operational state description for electric vehicles in order to establish a mutual understanding for the different possibilities of how vehicles can be operated. Furthermore, it is explored how the aggregating entity can be integrated into the current
1.2 Contributions

Concerning the integration of electric mobility into power systems the main contributions of the work can be identified as follows:

- An operational state description is developed which allows the classification and interconnection of envisioned PEV operation modes.

- Models based on a multi energy carrier approach are developed for individual PEVs. The models include single step and multi period optimizations. They allow to determine the energy consumption for PEVs when driving.

- An approach for PEV demand management in electricity networks is developed. It is based on game theoretical concepts and agent theory. The demand management scheme incorporates a distributed, predictive and hierarchical structure.

- The PEV demand management approach and the individual PEVs are integrated with an agent based transportation simulation tool. This combination allows to exploit detailed information of temporal and spatial vehicle behavior and battery energy levels.

- An aggregation method for vehicles providing V2G services is developed and integrated into the demand management scheme. It relies also on the transportation simulation output. It is able to balance the infeed errors of renewable energy sources (RES) or to provide ancillary services.

- The V2G balancing algorithm is integrated into the electric vehicle demand management method using the operational state description.
Chapter 1.

- The V2G balancing algorithm features a disaggregation method that schedules individual PEVs in order to perform the desired balancing services on the macroscopic level. The scheduling algorithm uses a heuristic. It fully considers the results attained from the demand management model and the physical network constraints.

- Finally, case studies are performed for a large metropolitan electricity grid. The studies rely on the vehicle models, the transportation simulation and the demand management scheme. The latter is integrated in the power system model. General effects of electric mobility on power systems are studied and include utilization levels of individual assets, mutation of load curves, analysis of voltage levels and the impact of V2G services on electricity networks.

1.3 Outline of the Thesis

The thesis is divided into the following Chapters which include separate, brief introductions.

Chapter 2 introduces the reader to organizational and operational aspects of power systems. The main, active entities are introduced. Furthermore, a novel entity called the aggregator is introduced. Its envisioned operational objectives are described. Finally, a framework is presented which integrates the aggregator into current power system organization and operation.

Chapter 3 contains a brief introduction to the subject of PEV control in power systems. It describes several possible applications and objectives. Subsequently, a general framework is derived which structures different possible operation modes and defines vehicle states.

Chapter 4 uses a multi energy carrier approach to model a single PEV. The developed model is used to optimize energy deployment while driving and allows to simulate a PEV in different operation modes. The model is formulated for a single step and for a multi period optimization.

Chapter 5 introduces agent based modeling for the management of PEV demand. Using game theoretical concepts, the agents strategic behavior in order to attain a potentially scarce good, here power, is
modeled. It is incorporated in an optimization setup. The mathematical framework for translating the agent’s bidding behavior into an optimization is presented. The optimization is performed by a platform referred to as PEV Manager which can be distributed in a network and be active on different voltage levels of the network.

Chapter 6 gives an introduction into the agent based transportation model which is used to determine the temporal and spatial behavior of the vehicles. An integration of the transportation model and the power system model, which includes the demand management scheme from the previous chapter is carried out. The integrated model is then used to perform case studies in a large metropolitan area electricity distribution system subject to large scale electric mobility. Implications on electricity network assets as well as possible future load curves are determined.

Chapter 7 develops a model predictive controller that is able to cluster and control PEVs in V2G mode. The controller and the PEVs in V2G mode are interlinked to the intelligent PEV demand management scheme. Case studies demonstrating the viability of V2G services are performed using the metropolitan case.

Chapter 8 provides a summary of the main findings and gives an outlook for possible future work.

1.4 List of Publications

The following papers have been published in the course of the work on this thesis:

Journal Papers


3. M. D. Galus and G. Andersson:  

4. M. D. Galus, M. Gonzalez Vaya, T. Krause, G. Andersson:  

5. L. Wehinger, G. Hug, M. D. Galus, G. Andersson:  


Integrating power systems, transportation systems and vehicle technology for electric mobility impact assessment and efficient control. Accepted to *IEEE Transactions on Smart Grids*, 2012.

8. M. D. Galus, S. Koch and G. Andersson:  

9. M. D. Galus, M. Zima, G. Andersson:  

1.4. List of Publications

Conference Papers

1. M. D. Galus, F. Wietor, G. Andersson:

2. M. D. Galus, S. Art, G. Andersson:

3. M. D. Galus and G. Andersson:

4. S. Chatzivasileiadis, M. D. Galus, Y. Reckinger and G. Andersson:

5. M. D. Galus, R. A. Waraich and G. Andersson:


7. S. Koch, M. D. Galus, S. Chatzivasileiadis and G. Andersson:


15. M. D. Galus, R. A. Waraich, M. Balmer, G. Andersson and K. W. Axhausen:

16. M. D. Galus and G. Andersson:

17. M. D. Galus and G. Andersson:

**Other Publications**

1. M. D. Galus, G. Georges, R. A. Waraich:
   Final Project Report: Abating Road Emissions Through Efficient Electric Mobility Interactions with the Electric System (ARTEMIS), (in German). ETH Zürich, Switzerland, 2012.

2. M. D. Galus and M. Schwabe:
Chapter 2

Integration of the PEV aggregator - a new entity - into power system operation

This chapter reviews the general concepts of power systems including technical and operational aspects. A new power system entity, called PEV aggregator, is introduced. It is envisioned to manage a large number of electric vehicles. Based on the description of current power system operational rules, a possible integration of the PEV aggregator into the established operational framework of power systems is elaborated. The existing framework is extended and interfaces between the PEV aggregator and established power system actors are defined. Finally, some implications of this new framework on current metering concepts are discussed.

2.1 Conceptual Overview of Electric Power Systems

Power systems have developed over the last century, resulting in different architectural designs and operation schemes in different countries. Due to political decisions, many electricity systems are nowadays liberalized. To this end, companies, which before were vertically integrated
Chapter 2. Integrating the PEV Aggregator

incorporating all segments of the electricity value chain, were unbundled. Furthermore, competition and free access to the electricity market were introduced [27]. The design and operation of liberalized systems is taken as the basis for the following considerations. Two different structures of power systems are of interest, i.e.,:

- The technical structure,
- The organizational structure.

2.1.1 Technical structure of power systems

The purpose of power systems is the generation, the transportation and the distribution of electricity to end consumers (EC). From the technical point of view, the structure of power systems can be defined to incorporate the following hierarchical layers:

- Generation,
- Transmission,
- Distribution,
- Consumption.

Traditionally, large generation blocks, like nuclear or fossil fueled, and hydro power plants inject power into the transmission system. The system must be dimensioned to accommodate these large amounts of power and transport them over long distances, e.g., ten to hundreds of kilometers. The transmission system can be said to act as the backbone of a power system. Interconnections between power systems of different countries are done dominantly on this level. In order to minimize resistive losses, the voltage levels of the transmission system are usually higher than 110 kV, in Europe most commonly 220 kV and 400 kV ($P_{\text{transmitted}} \sim \frac{P_{\text{transmitted}}}{U^2}$).

On a regional level, power delivery is carried out by distribution systems. These systems are connected to both high voltage transmission systems as well as lower voltage EC. The usual flow of power is from transmission systems via distribution systems towards ECs. However,
this principle is changing in many systems as increased numbers of dis-
tributed generation (DG) units, such as wind turbines or photovoltaic
systems, are connected at the distribution level. In some conditions, e.g.,
strong wind and low load, this can result in a reversed flow, where the
power flows from the distribution system to the transmission system.
The voltage levels in distribution systems range from 110 kV down to
400 V (commonly known as 230 V phase-to-ground, country dependent).

Consumers can be connected to any voltage level. However, at the lower
the voltage level less power can be transported. Hence, the level on which
the consumers are connected is dependent on the amount of consumed
power. Large industries with a significant consumption may draw their
power directly from the transmission network. Household consumers are
almost exclusively connected to the lowest voltage level.

The equipment used for power delivery is generally split into two types:

- Primary equipment,
- Secondary equipment.

Primary equipment refers to system components which carry high cur-
rents or are subject to high voltages. Their purpose is the transport
of the energy [28]. Typical examples are overhead lines, transform-
ers, switches, etc. Secondary equipment represents auxiliary devices
and systems for metering, monitoring, supervision, protection and con-
trol [29,30].

2.1.2 Organizational structure of actors in power systems

There are three issues that are of particular importance for the organi-
zational structure of power systems:

- Natural monopoly,
- Regulation,
- Competitive power markets.
Transmission and distribution networks/infrastructure are investment intensive and there is no benefit for a society in building several parallel and competing networks. Hence, the concept of natural monopolies is commonly accepted in this domain, resulting in one transmission system and several distribution systems, each of the latter serving a defined geographical area. Figure 2.1 illustrates the organizational structure of typical power systems in the ENTSO-E area of continental Europe. It displays the roles and actors. One actor might incorporate several roles. Deviations from this structure can occur [31,32].

The regulator avoids unfair exploitation of the natural monopoly possibly resulting in unjustified high prices for network usage. It monitors and approves prices for the transmission and distribution of energy allowing network owners to achieve reasonable profits. Furthermore, the regulator implements incentives for an economic operation of the system as well as transparent and fair access to the network for all market players. However, the entity does not directly determine electricity prices.

The Transmission System Operator (TSO), the Independent System Operator (ISO) and Distribution Companies (DisCos) operate the respective systems under rules approved by the regulator. Contrary to the ISO, the TSO not only operates but also owns the transmission assets in his area of supervision, which is called control zone. The control zone
does not necessarily have to relate to country borders but usually it does. The operation responsibility of the TSO/ISO is not limited to the transmission network, but rather the entire power system. The TSO controls the voltages and ensures system security through contracting ancillary services for its control zone. These are used to balance differences between generation and consumption in real time, thereby stabilizing the frequency.

Ancillary services are contracted by the TSO via a separate market [33] usually with relatively high prices [34]. The services are provided by primary-, secondary- and tertiary reserves [35,36]. The costs incurred by the TSO for keeping the network secure are included in the network usage fees.

Primary and secondary frequency controls are constantly active in order to keep the frequency stable within a small band around nominal frequency, i.e., 50 Hz in the ENTSO-E region. Primary reserves are activated locally at the generator based on a frequency measurement and a control loop. The reserves balance small and counteract large errors. In the latter case, primary reserves are only able to stabilize the frequency at another value than nominal frequency. Secondary reserves are employed to recover the frequency to the steady state value, releasing primary reserves. The secondary reserves are activated via an Automatic Generation Control (AGC) signal sent by the TSO [35,37,38]. Secondary reserves typically balance larger errors, e.g., errors from ramping, load forecasts or renewable energy infeed forecasts. Tertiary reserves are activated manually, rather rarely and are used during unforeseen, large, long lasting disturbances. Figure 2.2 gives an overview of different control reserves and their activation times in most ENTSO-E systems1 [39–43].

Generators, also referred to as Generation Companies (GenCos), and consumers participate in a power market, competing to sell and acquire power economically. Only large consumers act directly on electricity markets. The majority of consumers receives power from their suppliers, also called Energy Service Providers (ESPs), which aggregate consumer load. This aggregation leads to the minimization of fluctuating load behavior, a flattening of the load curve shapes and an increased load prediction reliability [44]. ESPs, and other wholesalers, frequently do not possess any generation assets. ESPs acquire electrical energy either

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1It can differ from other representations, such as the one found at ENTSO-E. Note that this is meant to be just a rudimentary representation.
Figure 2.2: General representation of timescales for frequency regulation control in most European countries [39].

directly from the market or from wholesalers. The latter can also be active on financial markets, not necessarily focusing on energy.

DisCos plan, operate and maintain the distribution networks. The DisCos are responsible for a good power quality and security of supply in their region. Furthermore, they are legally bound to procure all information and data necessary for ESPs and other participants, which the latter need to perform their energy accounting tasks. The information procurement also includes data in case ECs change their suppliers. The DisCos also determine costs for distribution network usage. The costs are passed to the energy service providers which further distribute them to their consumers [31].

Costumers are charged for the consumed electricity which is measured through metering services; see Fig. 2.1. The costs include the price of electrical energy, the network usage fee and balancing energy costs. The latter are derived from the difference between energy production and consumption schedules submitted by the BGM to the TSO and actual production and consumption of the particular Balance Group (BG) during the day of operation. This is explained in detail in the following section. The network usage fee covers investment and maintenance costs for electricity networks and the costs for ancillary services. The balancing energy and the cost for it are derived from the BGs [45].

2.1.3 The settlement of energy transactions and the balance group concept

Consumers (also ESP), producers as well as traders of electricity may group themselves in BG which are not necessarily affiliated to a specific
2.1. Conceptual Overview of Electric Power Systems

Figure 2.3: Illustration of a balance group with several feed-in and feed-out points.

ey

tographical area or DisCo within the control zone. The control zone may comprise many BGs as illustrated in Fig. 2.3.

A BG is a legal structure for accounting and billing purposes. No information on the network state is available to the BG. It consists of an arbitrary number of feed-in (generator) and/or feed-out (consumer) points. These are not necessarily spatially clustered or limited to the physical area which is supplied by a single distribution network [46]. Note that the BG might be considered similar to other concepts, such as virtual power plants [47–49]. However, the BG is only an accounting structure and must not be confused with other concepts.

The BG is managed by an entity, often called Balance Group Responsible (BGR) or Balance Group Manager (BGM), who takes over the administrative tasks of collecting information from loads, generators and traders. The aggregation taking place in BGs provides the advantage to the TSO of avoiding to communicate directly with a massive amount of actors. Furthermore, natural, uncontrollable load fluctuations can compensate each other allowing to perform forecasts more reliably [50]. In general, the communication costs and operational efforts are minimized and simpler accounting, related to balancing energy, is enabled. Typically, there are tens to hundreds of BG in one power system.
Day ahead, each BGM submits a BG schedule to the TSO. The schedules state how much energy will be exchanged with other BGs in each accounting time period. The accounting time period is often set to 15 minutes. The BGM calculates the energy exchanges by summing the predicted production setpoints of power generators in his BG area and the forecasted demand of his contracted consumers. The TSO uses the schedules to assess the feasibility of the announced schedules in relation to grid stability and grid congestions. In the event of non-compliance with system constraints, the TSO instructs the corresponding BGMs to modify their schedules before operation.

During operation, deviations from the submitted BG schedules are offset with balancing energy, which is procured by the TSO from contracted control power reserves provided by Ancillary Service Providers (ASPs). The procurement of ancillary services ensures the equilibrium between power generation and consumption in the control area.

At the end of the operation day, metering data allows the TSO to identify the amount of balancing energy delivered on behalf of each BG. The TSO then charges the BGM for this balancing energy based on the costs-plus principle. The BGM passes the costs on to his balance group members (traders, power suppliers and generators).

All market players have to be member of a BG or form their own BG to participate in the electric energy market. Thus, it is imperative for PEVs to belong to a BG as their energy demand or, in the case of V2G their energy supply, has to be accounted for in a BG schedule [32,46,51].

2.1.4 Metering data exchange and energy billing of end consumers

Production data and consumption data is measured and distributed to market entities in order to perform the accounting of energy delivery, of grid usage and of ancillary services. In most countries the DisCo is responsible for obtaining the metering data from EC. Hence, the DisCo installs, maintains and operates measuring equipment. The DisCo is legally obliged to record and aggregate all necessary data and forward the data to market players which require it for their specific purposes. The forwarded information differs for different market players which include the TSO, the BGM and the ESP. In general, metering is required at all feed-in and feed-out points of the network and at transfer points.
2.1. Conceptual Overview of Electric Power Systems

between grids. This is applicable for all voltage levels. In the following, the focus is on metering points in the distribution network. Thus, a metering point is defined to be a distribution grid point at which energy flows are metered and registered.

An integral part of the data interchange process is an unique, 33-digit metering point identification (ID) which is exclusively assigned to each metering point. This ID is in accordance with the rules of the union of Swiss Electric Utilities and ENTSO-E [52]. The alphanumeric number is of particular importance as it establishes the connection between the consumer, the metering location, a power supplier and the BG to which the supplier, i.e., ESP, belongs. The DisCo transmits data recorded at the metering point, which is assigned to a particular BG, to the respective BGM. The transmitted data comprises active and reactive power [52].

A generic example of how consumers are billed for their consumption is illustrated in Fig. 2.4. All metering points, indicated by the dots, are assigned to BG x which consists of two members, power supplier 1 and power supplier 2. For simplicity, no generators are connected in BG x. The metering points of the BG are all situated in the supervision area of one DisCo. Each power supplier contracts with several EC. During operation, the DisCo measures and records the aggregated load curves (LC) of the BG’s consumers. These LC are forwarded to the TSO which charges the BGM for the obtained balancing energy, i.e the BGM is

Figure 2.4: Meter data interchange for energy billing between grid operators and other market players.
charged for his forecast error. To allocate the balancing costs to the BG members, the BGM receives the LCs of each supplier. Furthermore, the power suppliers receive the LC of their EC to charge them for their energy consumption, for the grid usage costs which they induced, and finally for balancing energy costs.

It should be underlined that grid users, such as BGMs and power suppliers, only receive metered data. The BGM and the BG, as legal entities, do not have access to information on the network state. Only the TSO and the DisCos are aware of the state of their grids. Consumers belonging to the same BG can be distributed over several distribution networks each metered by the corresponding DisCo [51,53,54].

2.1.5 Grid operation and grid status of distribution networks

The DisCo is, amongst other things, responsible for the secure, efficient and reliable operation of its electricity network. Within the scope of grid operations, the entity identifies possible future congestions, plans network reinforcements and expands the grid [32,54].

In contrast to these long-term measures, the DisCo has access to some network data in order to determine the current grid status and to detect possible faults. During operation, the DisCo is able to alleviate congestions by performing switching actions. Power quality, i.e., desired voltage bands, is maintained by the variation of transformer tap positions. Network maintenance and expansion is performed on the basis of network configurations determined by grid studies.

In general, distribution systems are passive networks; while the DisCo controls the network it does not have control over the connected generators and only a limited control of the loads in the system. The latter is referred to as load management. It enables the DisCo to, without any prior notification, influence the demand of some interruptible appliances according to a predefined schedule. One example is the ripple control of storage water heaters. In case a secure operating state cannot be ensured by changing switch states or load management, the DisCo is ultimately allowed to temporarily disconnect network areas, including downstream distribution networks, or to request generators and EC to adjust their generation / consumption. Thus, reliable grid operation takes priority over the interests of individual market players.
However, the increasing penetration of information and communication technologies (ICT) in power systems may alter the passivity paradigm [55, 56]. Active distribution networks, often also referred to as smart grids, will enable more flexible network operation, facilitating the penetration of distributed energy resources such as flexible loads, including PEVs.

### 2.2 The PEV Aggregator Concept, tentative Operation Functionalities and Challenges

The concept of PEV aggregators has evolved as a possibility to integrate EVs and PHEVs into power market structures. The PEV aggregator is envisioned to cluster a large number of vehicles and perform market related tasks such as charging of the vehicles based on exogenous, market related price signals, forecasting the PEV load for BG schedules, bidding on ancillary service markets or providing ancillary services via V2G. The advantage of PEV aggregators is to facilitate the use of PEVs for ancillary services more easily. A good literature overview on aggregators is found in [11, 23, 24, 26, 38, 57–59]. In summary, the PEV aggregator is envisioned to incorporate functionalities which include but are not limited to:

- Acquisition of energy to charge electric vehicles
- Submission of BG schedules based on vehicle demand forecasts
- Charging of the PEVs according to their desires
- Support of distribution networks, i.e., ensuring proper voltage levels and asset loading levels
- Control of the charging behavior in order to attain valley filling
- Peak shaving through V2G services
- Aggregation of vehicles and bidding on ancillary service markets, e.g., for primary, secondary or tertiary control
- Balancing fluctuating RES infeed
Optimization techniques for scheduling the charging processes, either based on prices or network load (in the case of valley filling or peak shaving) often take into account information on the network state, the PEV state, i.e., battery state of charge (SOC) in percent, arrival, departure time and desired SOC at departure, as well as energy prices [16,60–63].

The required complete data set, which is needed to perform an efficient charging scheduling, is not available to any single entity of the power market framework depicted in Fig. 2.1. Many scheduling approaches are hardly implementable by the DisCos only. In the case of an emergency situation for the DisCo, such as transformer overloading, the DisCo could alter the charging schedule of electric vehicles in his area. However, since the DisCo could lack the information of which vehicle belongs to which BG, the DisCo could alter charging schedules determined by different BGMs in a discriminative way. That is, the DisCo could potentially shed more vehicles from one BG than from another and hence would actively change the consumption of the respective BG. This is legally not permitted. Moreover, the deviation from the predicted BG consumption would be penalized by balancing energy charges. These challenges have so far not been widely discussed by available PEV aggregator concepts [24,58].

Ancillary service procurement by PEVs suffers from similar problems. It remains unclear how network security can be guaranteed at all times whilst providing ancillary services, charging the vehicles and satisfying BG schedules. For example, simultaneous charging and V2G services could jeopardize the DisCo’s network security by temporally overloading network assets or by causing voltages to exceed the security limits in multiple places.

In the following, a framework for the PEV aggregator is derived. It fulfills the requirements of the liberalized market structures and at the same time addresses the technological and legal limitations of current power system organization.
2.3. Integrating the PEV Aggregator into Power Systems

Figure 2.5: The PEV aggregator and its integration into the organizational structure of power systems. The PEV aggregator can follow different objectives and incorporates interfaces to several established market players.

2.3 Integration of the PEV Aggregator into Power System Operation and its legal Framework

Existing actors incorporate already many functionalities which are desired for the operation of the PEV aggregator but no single one incorporates all. In the following, the PEV aggregator is envisioned as an independent entity. The envisioned relation of the PEV aggregator to the other market entities is illustrated in Fig. 2.5.

The PEV aggregator is assumed to be able to perform day ahead forecasts on transportation demand. It can be further assumed that the PEV aggregator takes advantage of recorded transportation data with adequate temporal and spatial resolution. Based on this information, the energy demand of its contracted fleet can be estimated for the next day. The required energy is purchased from a power supplier or directly
Chapter 2. Integrating the PEV Aggregator

from the wholesale market. The energy acquisition can take advantage of the charging flexibility provided by the PEVs, thereby minimizing the supply costs. Hence, the PEV aggregator can be envisioned to fulfill the role of a power supplier. Note that the PEV aggregator can also completely incorporate the roles of the supplier and the trader.

Assuming that the BGMs are able to detect deviations from the submitted schedules, which is possible with an adequate ICT infrastructure, the BGMs could counteract the deviations by employing appropriate measures. Such measures could be executed by the PEV aggregator. These services, often referred to as real time balancing (RTB) services, could reduce the deviation from the submitted BG schedule. Clearly, the BGM would need to compensate the PEV aggregator for such services. Compensations are indicated in the figure through the variable $\chi$. Vehicle owner participation in such services could be asserted by special consumer contracts.

Assuming a mixed BG of inflexible loads and the PEV aggregator, RTB services of the PEV aggregator, which are contracted by a different BG than the mixed BG in which the PEV aggregator is integrated, could cause deviations from the submitted schedule of the mixed BG. This would result in financial penalties for the mixed BG and hence, a conflict of interests could arise between the two member groups of the mixed BG: the PEV aggregator would be compensated for the RTB service, the other members would be penalized for the behavior of the PEV aggregator. Internal accounting needs to be implemented to solve this problem by allocating the additionally introduced deviations from RTB services to the PEV aggregator. However, this increases administrative complexity. It seems beneficial that the PEV aggregator should form an own BG and act as its BGM. First, all market players have to be members of a BG and, second, the RTB services can be either settled with the schedule deviations of the PEV aggregator or compensated through appropriate control of vehicle charging. Thus, besides being a power supplier, the PEV aggregator can be conceived to incorporate the role of the BGM.

In addition to RTB services, the PEV aggregator can be active on ancillary service markets. According to the contracts concluded, the PEV aggregator needs to control each car individually and either discharge or charge it, if possible. Note that only direct control is considered here [64]. The PEV aggregator’s control scheme should thereby incorporate the possibility for each car to quit the provision of V2G services and to
simply charge according to its demand. Such a framework is developed in Chapter 3. The immediate charging can cause deviations from the aggregator’s previously submitted schedule. Thus, the PEV aggregator, besides being a BGM, also needs to incorporate the role of the ASP.

The activities of the PEV aggregator, e.g., coordinating the charging of its vehicles for RTB, heavily effect the underlying electricity networks and can impose challenges to distribution network infrastructure. A load reduction concept can be utilized to avoid these challenges. For the concept, a request and bid scheme seems favorable in order to comply with the legally demanded non-discriminative rules. Load flows, based on very short term load forecasts, spatial and temporal PEV aggregator demand forecasts and currently metered data can be used to assess the network state close to real time. From these computations, the maximum available power at the different nodes during steady state operation can be computed. Incorporating the transformer ratings, the maximum loading of cables and voltage stability margins [65], constraints for PEV charging behavior as well as for V2G services can be derived.

In case a violation of the constraints is detected in area $\Lambda$, a PEV load reduction can avert asset damages and restore a secure operation mode. In such a case, the DisCo could send out a load reduction request to the PEV aggregator(s) active in the network. The request contains information about the required load reduction $\Delta P_{\text{request}}(t)$ as a function of time and the affected area where it should be enforced.

In reverse, the PEV aggregator calculates the maximum load $\Delta P_{\text{offer}}(t)$ which can be reduced and a monetary compensation which is calculated based on contracts with his PEV fleet, electricity price forecasts and balancing energy charges. The information is contained in a load reduction offer. The DisCo can reply with a load reduction confirmation message, containing the desired load reduction amount $\Delta P_{\text{confirm}}(t)$. This value can serve as an input to a management scheme which is able to reduce the total vehicle load efficiently by determining vehicles whose charging can be postponed. Such a scheme can be also applied in a hierarchical manner, where different load reduction requests are sent for different areas. It should be noted that such a load reduction scheme requires an appropriate ICT infrastructure in distribution networks.
Chapter 2. Integrating the PEV Aggregator

2.3.1 Adaption of metering concepts for PEV aggregator integration

In order to facilitate the operation of the PEV aggregator, the metering scheme, as it is implemented today, needs to be altered. PEVs, belonging to the PEV aggregator BG, may connect at different nodes, possibly in supply areas of different DisCos. Currently, grid nodes, i.e., metering points, are exclusively assigned to a power supplier and its BG. This hinders the accounting and the control of electric vehicles as required by the presented framework.

A potential solution for this problem is illustrated in Fig. 2.6. Here, a metering point can be simultaneously assigned to several BGs and the particular suppliers. A smart meter (SM) is a modern electricity meter that, compared with classical meters installed today, contains communication means for remote meter reading and new forms of inhabitant feedback [66–70]. It can be used to identify each connected PEV and to assign the PEV to the appropriate BG and power supplier pair. This is illustrated in the figure through different colors. Hence, several LCs can be recorded at one metering point. The DisCo delivers these LCs to the appropriate BGs and power suppliers for billing purposes.

Figure 2.6: Novel metering scheme which, with the aid of smart meters (SMs), allows the assignment of a metering point to several pairs of BG and power supplier.
2.4. Concluding Remarks

Such a well-defined separation between electric vehicle and charging as well as accounting infrastructure is referred to as the indirect accounting variant [71]. In the direct accounting variant the vehicle directly communicates with the accounting system, i.e., the DisCo, the BGM, etc. Recently, the indirect variant has been introduced into the German market [72]. It takes advantage of state-of-the-art ICT and the Europe-wide, standardized metering point labeling. The indirect accounting incorporates a system consisting of a charging station and an accounting software\(^2\).

2.4 Concluding Remarks

Liberalization of electricity markets and unbundling of the until recently integrated utilities is the main reason for the power system operation framework described in this chapter. In most European countries, the liberalization process is finished and similar structures as described in this chapter evolved. In the USA, structures are partly different but the main actors are the same. The metering schemes vary from country to country but correspond often closely. The proposed framework for the integration of the PEV aggregator might therefore need to be adapted for different countries.

Furthermore, as many operational aspects of the PEV aggregator are not ultimately defined, the herein discussed operational framework can be influenced by new concepts but also by new regulatory aspects and energy policy changes. Thus, the proposed solution for the integration of the PEV aggregator into power system operation is not an ultimate one but should be seen as a possible, flexible framework based on the current situation of regulatory rules, on good operational practice and on engineering experience. As juristical frameworks as well as operational practices can change over time and with new technological achievements, e.g., new ICT solutions, the PEV aggregator frameworks will need to be adapted.

\(^2\)Note that other solutions can be envisioned or are in operation in other countries, e.g., GSM in Sweden. It is likely that different accounting variants, with basically the same functionalities, will share the market.
Chapter 3

A PEV State Description enabling PEV Integration into Power Systems

This chapter introduces a PEV state description for the integration of PEVs into power system operation. The state description defines states that relate to the various operation modes which are envisioned for vehicles connected to the power system, e.g., the vehicles can be operated in an uncontrolled or controlled manner. The framework also links the various states by defining possible transition paths between the states of different modes. This allows to integrate the modes in one framework and to exploit the flexibility which is created by this integration while considering behavioral constraints of individual vehicles. The chapter illustrates also a simple example making a case for the application of this description.

3.1 Potential PEV Modes in Power Systems

As briefly mentioned in Chapter 1, PEVs can be differently utilized when connected to the power system. These possible utilization modes include being charged in an uncontrolled or in a controlled manner as well as V2G services. The latter includes the possibility to charge or discharge vehicles according to a specific objective. In the following, definitions of
the different envisioned PEV utilization schemes are given. The definitions are based on a brief literature overview. It comprises a condensed presentation of main findings related to the utilization schemes.

3.1.1 Uncontrolled charging

Uncontrolled charging refers to the situation where electric vehicles are considered as a passive load without any flexibility in their temporal and spatial charging behavior. In such mode, the vehicles simply arrive at their destination and, assuming the necessary infrastructure is available, connect to the power system in order to charge. In literature this is also referred to as "dumb" charging [73–75]. In the remainder of the thesis uncontrolled charging is used as the preferred term for this situation.

Several studies investigate the impact of large scale uncontrolled PEV charging on the power system. Besides investigating the impacts of uncontrolled charging on power generation portfolios [76–80], studies also looked into network effects on the transmission level [76, 77, 81] and on the distribution level [73, 82–88]. In brief, the results of the studies show that large scale uncontrolled charging of PEVs can alter locational marginal prices on the transmission level. Moreover, the charging can heavily stress distribution networks. In the latter case, asset overloading as well as violation of feasible voltage bands can occur.

3.1.2 Controlled charging

Controlled charging refers to the possibility to actively decide when and / or where the vehicles should be charged. Thus, the vehicles are considered as an active, i.e., flexible, load which can be shifted in time or in location. The control scheme which performs this shift can be assumed to be imposed by a PEV aggregator, already mentioned in Chapter 1. The entity is envisioned to cluster a large number of PEVs. It is assumed to be active on different power system markets including the ancillary service market and the power spot market. A detailed discussion of the PEV aggregator, its possible architecture, its various activities, and its integration and relation to other entities in power system planning and operation is found in [16, 23, 24, 26, 58].

Many studies investigate the advantages of shifting the load of PEVs into low load hours [89–93]. This is referred to as valley filling. Valley
3.1.3 V2G services

V2G services refer to the possibility of using PEVs as a distributed resource, i.e., as a storage. In such a case, the PEVs are envisioned to either charge or discharge their battery depending on a specific control objective. Controlled charging approaches which include the feedback of energy from the vehicle into the network, such as the combination of valley filling and peak shaving, are considered as V2G services. The V2G services are also assumed to be controlled by the PEV aggregator.

The V2G control objectives studied in the literature are manifold. One possibility is to use the PEVs for ancillary services [35, 39] in power systems. While [97] actually shows results from a field test using PEVs for ancillary services, [26,37] investigate the technical feasibility and [57, 98,99] look into the economic aspects of using the aggregated batteries for ancillary services. The economic studies find substantial added value when offering these services. Another possibility for V2G services is to use the aggregated storage of PEVs for balancing the infeed error of RES [12, 25,100–102]. Promising results are also found when looking into profit maximization of an individual PEV or of an aggregator by buying electricity at low prices and selling it during high price periods [62,103,104]. However, many of the studies, such as [26,98,102], pursue their analysis on a macrolevel without considering the constraints of individual vehicles imposed by their SOC, by their departure time and by their location in the distribution network.

3.2 The PEV state description

The possible utilization schemes, the control objectives and thus the different actions which can be undertaken by the vehicles are manifold. Therefore, it is necessary to establish a common understanding of
the utilization scheme, i.e., operation mode, and the particular state in which an individual PEV may be when connected to the power system.

Literature, which investigates V2G services, controlled and uncontrolled charging, do not describe the coupling of these different modes. The implications of the different modes are often analyzed individually without allowing vehicles to switch between the different possible modes, i.e., stop supplying V2G services and start charging. However, this option can be crucial because PEVs could need to stop the provision of V2G service in order to attain their desired SOC before departure. The lack of such an option calls for a framework embracing the different utilization schemes.

The framework developed in the following incorporates the power system point of view while the PEV is connected to it. Hence, it is analogous to the well known power system state description, found in [105], which defines the states Normal, Alert, Emergency, In extremis and Restoration as well as transfers between them.

While [106] suggested several possible states for an individual vehicle, Fig. 3.1 defines a state description for a PEV from the power system point of view. The states are defined depending on different battery energy level conditions and the modes in which the PEVs can be connected to the power system. As for the battery, the energy level of the PEV battery can either be constant, decreasing or increasing. These battery energy level conditions are denoted at the top of the Fig. 3.1. The PEV operation modes are given on the right hand side of Fig. 3.1 and include uncontrolled and controlled charging as well as V2G services. Hence, a matrix is formed, visualized by the dashed lines, in which different PEV states can be distinguished from each other. Possible transitions between states are indicated by the arrows in Fig. 3.1. The functionality of the framework is described in the following alongside the PEV operation modes.

### 3.2.1 The uncontrolled charging mode

It is obvious that the main purpose of vehicles, and therefore also of PEVs, is individual transport. When being used for transportation, the battery energy level of the vehicles is typically decreasing to an extent defined by the characteristics of the particular trip. Note that the control of the powertrain of different PEV models can also allow for charging the
3.2. The PEV state description

<table>
<thead>
<tr>
<th>Battery Energy Level</th>
<th>PEV Operation Mode</th>
</tr>
</thead>
<tbody>
<tr>
<td>Decreasing</td>
<td>V2G</td>
</tr>
<tr>
<td>Constant</td>
<td>Controlled</td>
</tr>
<tr>
<td>Increasing</td>
<td>Uncontrolled</td>
</tr>
</tbody>
</table>

- **[State 1]** Driving
- **[State 2]** Stand By
- **[State 3]** Charging
- **[State 4]** Waiting
- **[State 5]** Charging
- **[State 6]** Feeding Power
- **[State 7]** Idle
- **[State 8]** Drawing Power

Figure 3.1: Operation states of PEVs in system operation of the PEV aggregator.

Vehicle while driving. When driving, no connection to the power system can be established. Such situation is represented by the *Driving* state in Fig. 3.1. This state can be considered as the interface between the power system and the transportation system. This state is decoupled from the network view. However, it is allocated to the uncontrolled operation mode.

A transition from *Driving* into the uncontrolled *Stand By* state can be defined. In general, no influence on PEVs can be exerted when they are in the *Stand By* state. The *Stand By* state embodies the situation of a grid connected vehicle with a full battery. The PEV could also be not connected to the power system, i.e., parking at a location where no connection infrastructure is available. The PEV can leave this state by disconnecting and going back into the *Driving* state.

The third possible state in the uncontrolled PEV operation mode is the uncontrolled *Charging* state. Here, the vehicle is connected to the grid at arrival and the battery is not completely full. The battery is then charged but no external control actions are undertaken. The charging of the vehicle then lasts until the battery is full. When fully charged, the vehicle transfers from the uncontrolled *Charging* state into the *Stand By* state.
Chapter 3. A PEV State Description

state until it is disconnected and departs. Obviously, a transition from uncontrolled Charging to the Driving state is also possible, because the owner might simply disconnect the vehicle when leaving, even if the vehicle is not completely charged. In summary, this mode does not presume any coordinative control actions at all. Thus, the influence on the power system is solely driven by the largely unpredictable behavior of PEV users.

3.2.2 The controlled charging mode

A transition from the Driving state into the controlled operation mode can be envisioned as well. In order to be classified for this mode, the vehicle needs to be connected to the grid, be equipped with an adequately intelligent connection module and somehow be legally bound, e.g., contracted for controlled charging. Two states, similar to the uncontrolled operation mode, can be defined here. The difference to the uncontrolled operation mode is, however, that both states can be accessed and controlled by an entity such as the aggregator.

The Waiting state is similar to Stand By state. The battery energy level is stable in both cases. However, the states differ from each other because when a vehicle is in the Waiting state, the car does not yet have to be completely charged. The controller of the entity, which manages the car, decides that the vehicle should not be charged further. A transfer back to the Charging state is possible.

The Charging state in the controlled charging mode is analogous to the Charging state in the uncontrolled operation mode as the energy level of the battery is increasing. However, the charging of vehicles in this state can be controlled. If the network should face challenges due to excessive PEV load or another emergency situation, a control action can be undertaken and the vehicle’s charging power can either be adjusted or charging can be completely interrupted. Thus, this Charging state is assumed to take the particular network state into account. When charging is halted, the vehicle state changes from the Charging state into the Waiting state. Frequent transitions between both states are possible depending on the control objective of the managing entity and on the physical constraints of the electricity network.
Once completely charged to the desired SOC, the vehicle can perform a transition to the \textit{Stand By} state. Then, the PEV leaves the controlled operation mode and can, from now on, not be accessed by the controller until departure. Transitions from the \textit{Charging} state or the \textit{Waiting} state directly to the \textit{Driving} state are also possible by simply disconnecting the PEV from the grid and leaving. This is illustrated by the transition path from the \textit{Waiting} state over the controlled \textit{Charging} state to the \textit{Driving} state.

A transition from the controlled to the uncontrolled operation mode is also possible for PEVs in the \textit{Waiting} state. This transition represents a case where the car owner requires energy immediately. The transition path offers the possibility to exit from the controlled operation mode in order to simply charge the vehicle in an uncontrolled manner. Clearly, the possibility of leaving the controlled operation mode needs to be included in the contracting rules of the managing entity. It should also be included in the energy consumption forecast of the aggregator. In any case, the energy flow in this mode as well as in the uncontrolled operation mode is unidirectional - from the power grid to the PEV.

\subsection{3.2.3 The vehicle to grid mode}

V2G services constitute the third operation mode to which the vehicles can transfer from the \textit{Driving} state. This mode also requires intelligent connections to the power grid. V2G services incorporate three different states, one state more than for controlled charging, because here the battery energy level can also be decreasing. The V2G operation mode comprises the states \textit{Feeding Power}, \textit{Idle} and \textit{Drawing Power} as shown in Fig. 3.1. The cars which are inserted into the V2G mode can be assumed to be in the \textit{Idle} state when connecting to the power system. The next state is chosen dependent on V2G management algorithms and the particular state transitions are performed. The transitions and PEV states in the V2G mode are presumed to take the network state, i.e., line capacities and voltage constraints, fully into account. This is similar to the controlled charging mode. For example, a PEV should not transfer into the \textit{Drawing Power} state when it is parked in an already congested area.

The V2G mode differs from the controlled charging mode because it follows different objectives, so far not ultimately defined in literature.
Transitions between the controlled charging and the V2G mode can be envisioned but are not imperative. The cars could possibly leave the V2G mode in order to be sufficiently charged before departing. This charging can be assumed to be performed in a controlled manner. The controlling entity, i.e., the aggregator, would charge the vehicles dependent on the entity’s objective and considering the electricity network state. Hence, the aggregator would have the possibility to stop some other vehicle from charging in order to allow the vehicle, which just recently transferred from the V2G mode, to charge while keeping the local network in a secure state.

Further, the vehicle can also leave the V2G mode and charge in uncontrolled mode until the demanded SOC is reached. This transition is different to the one before as then no further influence can be exerted by the managing entity. The state transitions offer the important possibility to quit V2G services if the services intervene with energy and transportation demands of the particular car owner. The availability of the exit option could depend on special contracts between the PEV aggregator in charge of V2G services and the vehicle owner. Transitions between the states of the V2G, the controlled and uncontrolled operation mode have to be considered during planning stages of the managing entity.
The two modes of controlled charging and V2G services can be seen as the part of the framework where PEVs are actively dispatched between operational states. The dispatch can be envisioned to be based on the individual PEV state, the particular operation mode, the utilized algorithms and the objectives of the managing entity, i.e., the PEV aggregator. Figure 3.2 shows the area of active dispatch, e.g., exogenously controllable states (State 4 - State 8) in the dotted area. The states within the area can be used for advantageous integration of individual transportation into power system operation and planning, i.e., they allow to exploit the flexibility inherent to the vehicles as parking times are usually longer than charging times [107].

3.3 Example for the Framework Application

In order to illustrate the usefulness of the framework developed in Section 3.2.1-3.2.3, two simple cases, which apply the operational state description for PEVs, are investigated and compared.

The simulated system comprises a simple network of four nodes to which the PEVs connect. A fleet of in total 30'000 PEVs is simulated. The vehicles incorporate a departure time, a desired SOC at departure, a 3.5 kW power connection and a 30 kWh battery. Their temporal behavior has been simulated through a transportation micro-simulation [99] for a typical work day in a transportation network including 28’000 streets. The details of the transportation simulation are not of importance here and are explained in Chapter 6. The temporal behavior assumes that all PEVs are connected at the beginning and the end of the simulated day. The individual SOC always lies between 20% and 100%.

Two cases are studied according to the framework of Fig. 3.2 in order to demonstrate its applicability and are defined as:

Case 1: V2G services are performed without allowing a PEV state transfer to the uncontrolled operation mode.

Case 2: V2G services are performed allowing a PEV state transfer to the uncontrolled operation mode.
(a) Case 1: PEV operational state description without enabled V2G-uncontrolled charging transfers.

(b) Case 2: PEV operational state description with enabled V2G-uncontrolled charging transfers.

Figure 3.3: Difference between the operational state descriptions of the two examples.

Figure 3.3 illustrates Case 1 and Case 2 using the operational state description framework. In Case 1, illustrated in Fig. 3.3(a), uncontrolled Charging and the V2G service are decoupled. The vehicles which exit the V2G service do not transfer to the uncontrolled operation mode in order to achieve their desired SOC at departure. The cars simply depart, partly without having a sufficient SOC. These vehicles do not impose load on the system after V2G provision.

Case 2 introduces a transition path between V2G services and the uncontrolled operation mode. This case is illustrated in Fig. 3.3(b) through the grey circles. Now, PEVs are able to quit V2G services in order to be sufficiently charged in the uncontrolled charging mode. The transfer back to the V2G mode could be possible but is not included in the example for simplicity.

Both cases allow for immediate departure. Furthermore, the transfer from the uncontrolled Charging state to the Stand By state is included in the simulation to incorporate the possibility that PEVs have been fully charged within the uncontrolled mode but have not yet departed.

Two types of PEVs are considered within the fleet. One is in uncontrolled Charging only, when connected to the network. The share of vehicles in this mode covers 30% of the cars. The other 70% of the vehicles are assumed to provide load frequency control, i.e., secondary control [39].
A control signal which is transmitted by the TSO is used as an input signal for the PEVs. The signal is depicted in Fig. 3.4. The per unit value of the signal determines the actual power to be delivered to or drawn from the storage which consists of the PEVs in V2G mode. A symmetrically contracted power of 4 MW is assumed for the PEV fleet in V2G mode. Positive signal values mean that PEVs need to be discharged, negative that they need to charge. Hence, according to Fig. 3.1, the vehicles switch between the states 6–8. Zero net energy usage for load frequency services is not assumed as can be observed in Fig. 3.4. The utilized load frequency control signal is negatively biased. This bias poses an advantageous situation for the PEVs in V2G mode as it implies that the vehicles are charged on average throughout the day. However, with connection intervals shorter than 24 hours, it is possible that the net energy, which needs to be supplied by the vehicles in V2G mode, is positive during a specific connection interval. Then, on average, the PEVs would need to supply more energy to the grid than they would receive.

After a time interval of 15 minutes the SOC of the vehicles in V2G mode is assessed and it is decided whether they need to charge immediately in order to achieve their desired SOC before the anticipated departure time. Should this be the case, the particular vehicle quits V2G service in Case 2 and transfers into the uncontrolled operation mode.

The goal of the simulation example is to show that there is a difference between considering operation mode transitions, which take into account individual transport demands, or neglecting them. The implications are illustrated in Fig. 3.5. Figure 3.5(a) shows the base load in the network through the dotted, light grey graph. The load is assumed to be predominantly residential. The shape shows low load during the night and high load in the evening hours. The peak between 22:00 and 23:00 is due to time of use pricing and ripple control of household water boilers being switched on during this time. The curve is representative for about 130'000 households.

The black, dashed line illustrates the load in Case 1. The load includes uncontrolled charging of PEVs without considering a transfer from V2G into the uncontrolled charging mode for immediate charging. The cars contracted for V2G services (70% of the fleet) supply the secondary control service until they leave, no matter if the individual car attains its desired SOC or not.
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Figure 3.4: TSO secondary control signal in 5 second intervals.

Figure 3.5: Effect of PEV transfer from V2G to controlled charging.
(a) Load curves for system base load (bright grey), total load including PEVs without V2G transfers (dark grey) and with V2G transfers (black).
(b) Difference between the loads with and without V2G transfer.
3.4. Concluding Remarks

For Case 1, the overall load level is higher than the base load and the shape of the load curve is altered. It can be seen that vehicles, which connect in the uncontrolled charging mode, predominantly charge during the night before leaving to work. At work they connect immediately and charge again in order to attain a SOC that is sufficient to reach their home. It is assumed that they need to charge 10% more energy than used on the way to the working place. At home they start to charge again.

The black graph in Fig. 3.5(a) shows the load curve of Case 2. Here, the state transfer from the V2G to the uncontrolled operation mode for immediate charging is possible. The transitions defined by Fig. 3.3(b) are performed by PEVs in order to be charged adequately before departure. Obviously, the resulting load on the system is different than in Case 1. Load shape and level are altered. The difference between the two cases is plotted in Fig. 3.5(b). The difference is substantial even for the relatively low PEV penetration simulated here. 30’000 PEVs for 130’000 households equals a penetration rate of about 23%.

The example stresses several important things relating to the developed framework. First, it is important to take into account the energy desired for the future individual transportation demand of PEVs in V2G mode. This ensures that the vehicles can reach their next destination. The operational state description, in contrast to other approaches which are limited to only one operation mode, is able to consider such limitations. Secondly, allowing vehicles to transfer from one operational mode to another leads to variations in load curves and alters the energy consumption schedule of the managing entity. Both facts need to be considered in power system planning and operation. Otherwise, the demand for balancing energy could increase substantially as load forecast errors would grow. Finally, the example shows that the application of the developed framework allows for a high flexibility and accuracy of PEV management as the operational limitations of individual PEVs are considered.

3.4 Concluding Remarks

Using an overview of much of the recent literature on PEV operation, the chapter provides a description of tentative, envisioned operation modes for PEVs when connected to power systems. The overview shows
that operation modes can follow different objectives and that models, investigating the effects of the different modes on the generation and network side, often only consider the respective mode.

The chapter argues that when aspiring to power system wide objectives, e.g., balancing RES with V2G, the demands of the individual vehicles should not be neglected. That is, the vehicles should still be able to attain the desired SOC at departure. This might interfere with the power system objectives of the PEV aggregator controlling PEVs in a particular mode. Therefore, the chapter developed an operational state description which clearly delineates the different PEV operation modes. The delineation defines individual states for each mode and possible transfers between states and modes to increase the flexibility of the framework.

The application of the framework could enable the PEV aggregator to follow different power system dependent objectives while fully considering the individual PEV constraints. However, it remains to be investigated how the framework can be used in current power system operation practices. The flexibility, which the PEV aggregator is able to exploit, needs to be considered when performing day ahead planning and submitting BG schedules. The example provided in the last section of this chapter underlines this point. The large demand differences between Case 1 and Case 2 of the given example need to be considered in the PEV aggregator’s BG schedules as otherwise large, financial penalties would be encountered.
Chapter 4

Modeling a PEV using a Multi Energy Carrier Approach

This chapter introduces the multi energy carrier modeling approach for PEVs. After developing a general model for PEVs, it is adjusted for a specific PEV type. A single step, linear optimization scheme is applied to simulate PEVs which are driving. The simulations are used to show the feasibility of the multi energy carrier approach for modeling PEVs and to calculate the energy consumption of the vehicles. The single-step optimization is extended to a multi period optimization in order to calculate the best possible utilization of the energy carriers on board. Finally, the single step and the multi period optimization are compared in terms of total energy consumption.

4.1 Brief Introduction to the Energy Hub Concept

The modeling approach of energy hubs has been developed and facilitated in order to analyze energy systems which utilize multiple energy carriers such as electricity, gas, and hydrogen. In specific, the energy hub approach allows to investigate potential synergies between the different energy carriers used in a system by allowing interconnections of energy carrier networks incorporating appropriate converters [108].
Chapter 4. Modeling a PEV as an Energy Hub

An energy hub is defined through several attributes like inputs, outputs as well as energy conversion and storage devices [109]. With respect to different input energy carriers \( \epsilon_1 \) and \( \epsilon_2 \), the complete set of energy carriers is denoted \( \mathcal{E} \). Furthermore, each hub \( h \) contains a set of converters \( \mathcal{C}_h \). The subset \( \mathcal{C}_{h\epsilon_1} \subseteq \mathcal{C}_h \) contains all converter elements of hub \( h \) which convert \( \epsilon_1 \) into another carrier, thus:

\[
\epsilon_1, \epsilon_2, \ldots, \epsilon_E \in \mathcal{E} = \{ \text{electricity, hydrogen, \ldots} \} ,
\]

and

\[
c_{\epsilon_1, \epsilon_1}, c_{\epsilon_1, \epsilon_2}, \ldots, c_{\epsilon_1, \epsilon_E} \in \mathcal{C}_{h\epsilon_1} .
\]

The hub equation without storage is formulated according to

\[
\begin{bmatrix}
L_{\epsilon_1} \\
L_{\epsilon_2} \\
\vdots \\
L_{\epsilon_E}
\end{bmatrix}
= 
\begin{bmatrix}
c_{\epsilon_1, \epsilon_1} & c_{\epsilon_2, \epsilon_1} & \cdots & c_{\epsilon_E, \epsilon_1} \\
c_{\epsilon_1, \epsilon_2} & c_{\epsilon_2, \epsilon_2} & \cdots & c_{\epsilon_E, \epsilon_2} \\
\vdots & \vdots & \ddots & \vdots \\
c_{\epsilon_1, \epsilon_E} & c_{\epsilon_2, \epsilon_E} & \cdots & c_{\epsilon_E, \epsilon_E}
\end{bmatrix}
\begin{bmatrix}
P_{\epsilon_1} \\
P_{\epsilon_2} \\
\vdots \\
P_{\epsilon_E}
\end{bmatrix},
\]

where \( \mathbf{L} \), \( \mathbf{P} \) and \( \mathbf{C} \) are the load vector, the input vector and the conversion matrix, respectively. The coupling matrix consists of coupling factors \( c_{\epsilon_1, \epsilon_2} \) converting one energy carrier into another one. The coupling factors include the efficiencies of the converters located in the particular power path.

With respect to storage, the storage interface can be modeled similar to a converter device with steady-state input and output power values \( \dot{E}_{\epsilon_1} \) and \( \eta_{\epsilon_1} \), where \( \eta_{\epsilon_1} \) expresses the efficiency of the charging/discharging interface. It is given by

\[
\eta_{\epsilon_1} = \begin{cases} 
\eta_{\epsilon_1}^+ & \text{if } \dot{E}_{\epsilon_1} \geq 0 \quad \text{(charging/standby)} \\
1/\eta_{\epsilon_1}^- & \text{else} \quad \text{(discharging)}
\end{cases}
\]

The stored energy after a certain operation period \( T \) equals the initial storage content plus the time integral of the power stored into the device. For steady-state considerations, power can be approximated by the change in energy \( \Delta E_{\epsilon_1} \) during a time period \( \Delta t_{\text{op}} \), assuming a constant slope \( \dot{E}_{\epsilon_1} = dE_{\epsilon_1}/dt_{\text{op}} \). Therefore, the energy in the storage in time interval \( T \), can be expressed as

\[
E_{\epsilon_1}(T) = E_{\epsilon_1}(T-1) + \int_{T-1}^{T-1+\tau(T)} \dot{E}_{\epsilon_1}(t_{\text{op}}) \, dt_{\text{op}} \approx E_{\epsilon_1}(T-1) + \Delta E_{\epsilon_1} ,
\]

(4.5)
where, \( \dot{E} \) is the power weighted by the storage interface efficiency. Note that \( \tau(T) \) gives the length in seconds of the the operation period \( T \). The parameter \( t_{op} \) expresses an infinitesimal operation time step of the hub.

Adding the storage to the hub equation (4.3) and taking the location of the storage within the hub into account, one can rewrite the equation in a more condensed way as

\[
L = \left( \begin{array}{cc}
C & -S \\
\dot{E} & P
\end{array} \right),
\]

(4.6)

where \( S \) is the storage coupling matrix. Its entries are the coupling factors multiplied by the storage interface efficiencies of the particular power paths. The storage vector is represented by \( \dot{E} \) and contains different storages and their respective power input / output. A detailed derivation of the energy hub modeling technique can be found in [108–110].

### 4.2 Modeling PEVs as an Energy Hub

PEVs, unlike vehicles using a combustion engine, can be in various operating states, which are elaborated in Chapter 3. From the individual vehicle’s point of view, the states in which the vehicles are actually performing an activity consist of Driving (D), of uncontrolled Charging (UC), of controlled Charging (CC), of offering ancillary services through V2G (V2G) and of refueling (RF). The states are included in the set

\[
\Xi = \{ D, UC, CR, V2G, RF \}.
\]

(4.7)

It should be noted that the V2G state in this chapter, i.e., in the energy hub model, pools the states Drawing Power, Idle and Feeding Power from the framework of described in Chapter 3. As the operational state description is developed from a power system point of view, the refueling state is neglected. However, for developing a model of an individual PEV it needs to be considered.

In order to integrate the states into a hub model described in the previous paragraph, an operating state decision function incorporating symbolic variables can be derived according to

\[
\mathcal{E}(\Xi) = \frac{\partial}{\partial \Xi} \left( D \ UC \ CC \ V2G \ RF \right).
\]

(4.8)
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For example, during a driving situation the function $E(D)$ becomes

$$E(D) = \frac{\partial}{\partial D} \left( D \ UC \ CC \ V2G \ RF \right),$$

and hence

$$E(D) = \left( 1 \ 0 \ 0 \ 0 \ 0 \right).$$

The kinetic load for the PEV energy hub model in the Driving state is calculated through Newton’s 2nd law given by

$$E = \left( MgvC_r + \frac{1}{2}\rho_{air}C_DA_fv^3 + \delta Mv\dot{v} + Mg\sin(\Phi) \right)t_{op}.$$  

In the PEV hub model, the load is not a vector but a single value. Here again, $t_{op}$ stands for the operation time of the PEV energy hub. For the PEV energy hub, the time step length of operation is chosen to be one second if not stated otherwise. In (4.11), $M$ is the mass, $v$ is the speed, $C_r$ is the tire friction coefficient, $A_f$ is the cars front area, $C_D$ is the car air resistance coefficient, $\rho_{air}$ is the air density, $\delta$ is the vehicle mass coefficient and $\sin(\Phi)$ is the road’s grade. The variables are quantified in Table A.1 in Appendix A for a specific PEV. This equation can be used to calculate the load for different drive cycles. Such cycles represent differing driving behaviors with different average and maximum speeds [111,112].

The general energy hub formulation given in 4.6 has to be reformulated to account for the peculiarities of PEVs. Figure 4.1 displays the typical converter arrangement for a Series-PHEV [113] in the grey area\(^1\). The

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\(^1\)It should be noted that different converter architectures and operation possibilities are possible. The Series-PHEV setup is one common, rather simple architecture. It can also be called "range extender". Other converter setups are found in [113].
4.2. Modeling PEVs as an Energy Hub

figure defines the power paths through which the kinetic load needs to be met. The white area indicates a possible extension using a fuel cell and a hydrogen tank. Such a possibility is investigated in [114]. This extension is neglected for shortness, herein. In the following a PEV energy hub model is developed for a Series-PHEV and can be formulated according to

\[ L(t_{\text{op}}) = E(\Xi) \left( C(L(t_{\text{op}})) - S(L(t_{\text{op}})) \right) \left( \frac{P(t_{\text{op}})}{\dot{E}(t_{\text{op}})} \right), \]  

(4.12)

with

\[ C(L(t_{\text{op}})) = \begin{pmatrix}
    c_{el\, kin\, D}(L(t_{\text{op}})) & c_{gaso\, kin\, D}(L(t_{\text{op}})) & 1 \\
    c_{el\, kin\, UC} & c_{gaso\, kin\, UC} & 0 \\
    c_{el\, kin\, CC} & c_{gaso\, kin\, CC} & 0 \\
    c_{el\, kin\, V2G} & c_{gaso\, kin\, V2G} & 0 \\
    c_{el\, kin\, RF} & c_{gaso\, kin\, RF} & 0 
\end{pmatrix}, \]  

(4.12a)

\[ S(L(t_{\text{op}})) = \begin{pmatrix}
    \frac{\eta_{el}}{c_{el\, kin\, D}} & \frac{\eta_{gaso}}{c_{gaso\, kin\, D}} \\
    \frac{\eta_{el}}{c_{el\, kin\, UC}} & \frac{\eta_{gaso}}{c_{gaso\, kin\, UC}} \\
    \frac{\eta_{el}}{c_{el\, kin\, CC}} & \frac{\eta_{gaso}}{c_{gaso\, kin\, CC}} \\
    \frac{\eta_{el}}{c_{el\, kin\, V2G}} & \frac{\eta_{gaso}}{c_{gaso\, kin\, V2G}} \\
    \frac{\eta_{el}}{c_{el\, kin\, RF}} & \frac{\eta_{gaso}}{c_{gaso\, kin\, RF}} 
\end{pmatrix}, \]  

(4.12b)

and

\[ P(t_{\text{op}}) = \begin{pmatrix}
    P_{el}(t_{\text{op}}) \\
    P_{gaso}(t_{\text{op}}) \\
    P_{dis}(t_{\text{op}}) 
\end{pmatrix}, \quad \dot{E} = \begin{pmatrix}
    \dot{E}_{el}(t_{\text{op}}) \\
    \dot{E}_{gaso}(t_{\text{op}}) 
\end{pmatrix}. \]  

(4.12c)

Example: The PEV energy hub equation in the driving state D is expressed using the above stated mathematical framework as:

\[ L(t_{\text{op}}) = E(D) \left( C(L(t_{\text{op}})) - S(L(t_{\text{op}})) \right) \left( \frac{P(t_{\text{op}})}{\dot{E}(t_{\text{op}})} \right), \]  

(4.13)

which gives

\[ E(D)C(L(t_{\text{op}})) = \begin{pmatrix}
    c_{el\, kin\, D}(L(t_{\text{op}})) & c_{gaso\, kin\, D}(L(t_{\text{op}})) & 1 
\end{pmatrix}, \]  

(4.13a)
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and

\[ E(D)S(L(t_{op})) = \left( \frac{c_{el \, kin \, b}(L(t_{op}))}{\eta_{el}} \cdot c_{gaso \, kin \, b}(L(t_{op})) \cdot \eta_{gaso} \right), \]  \hspace{1cm} (4.13b)

with

\[ P(t_{op}) = \begin{pmatrix} P_{el}(t_{op}) \\ P_{gaso}(t_{op}) \\ P_{dis}(t_{op}) \end{pmatrix}, \quad \dot{E} = \begin{pmatrix} \dot{E}_{el}(t_{op}) \\ \dot{E}_{gaso}(t_{op}) \end{pmatrix}. \]  \hspace{1cm} (4.13c)

The general energy hub equation is multiplied by the operating state decision function \( E(\Xi) \). This multiplication allows to choose the particular power flow coupling option which is appropriate for the current PEV operation state. The vector \( P(t_{op}) \) denotes the input vector of the PEV energy hub. The values of the vector depend on the time step size \( t_{op} \) and the PEV state, respectively. Obviously, an input cannot be apparent when the vehicle is driving because it is not connected to an infrastructure, i.e., the electricity network, which could provide it. In this case, the power needed for propulsion is drawn from the onboard storages such as the battery. The power drawn from the battery and the gasoline tanks is denoted \( \dot{E}_{el}(t_{op}) \) and \( \dot{E}_{gaso}(t_{op}) \), respectively.

The electric input \( P_{el}(t_{op}) \) can only be nonzero if the PEV is connected to the power system. In fact, once it is connected, the electric input can be either only positive or be alternating between positive and negative values depending on whether the PEV is only charging or in use for V2G services. The kinetic load will obviously be zero if the vehicle is operated in one of the latter modes because it is parked.

The refueling state can be modeled accordingly. Here, only \( P_{gaso}(t_{op}) \) will be nonzero and positive. The refueling state can be integrated into the Stand By state of the framework in Chapter 3. The dissipated power \( P_{dis} \) is the only input variable which can be nonzero while driving. This variable is negative or equal to zero as it models dissipated power. In other PEV states, this variable is not relevant. Table 4.1 summarizes the input vector and load values for the different PEV states.

In (4.13a), \( c_{el \, kin \, b}(L(t_{op})) \) denotes the coupling factor for the power path starting from the electricity input or the electricity storage to the kinetic load. The path is active when the PEV is in the driving state. The factor is composed of the efficiencies representing the converters in
4.2. Modeling PEVs as an Energy Hub

Table 4.1: Operating state dependency of inputs and load.

<table>
<thead>
<tr>
<th>State</th>
<th>In-, Output</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>D</td>
<td>$P_{el}(t_{op})$</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>$P_{gaso}(t_{op})$</td>
<td>0</td>
</tr>
<tr>
<td>UC,CC,V2G</td>
<td>$P_{gaso}(t_{op})$</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>$L(t_{op})$</td>
<td>0</td>
</tr>
<tr>
<td>RF</td>
<td>$P_{el}(t_{op})$</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>$L(t_{op})$</td>
<td>0</td>
</tr>
</tbody>
</table>

the particular power flow path. The coupling factor, i.e., the converter efficiencies, are dependent on the kinetic load in $t_{op}$, which is indicated by $L(t_{op})$. This enables the integration of nonlinear motor efficiencies. For simplicity, the converter efficiencies are assumed to be constant in cases where the PEV consumes energy.

Regenerative breaking, where energy is recaptured through the electric motor acting as a generator when breaking, is taken into account in the model. Adapting the coupling factor of the particular power path can consider the efficiencies of the generator and the battery. They are different than in a case when the car consumes energy. In the other operating states, the coupling factors are assumed to be independent of the load and thus are left constant.

In order to ensure a correct, state dependent, power flow within the PEV hub, the coupling factors for charging, V2G and refueling are set in $C(L(t_{op}))$ to zero or to one. This is done because of the following rationale. For example, when offering V2G services, there cannot be a power flow between the grid and the gasoline tank. The electricity input needs to be directly related to the battery of the PEV as the demanded/offered power from/to the grid needs to be supplied from the battery, only. In case of refueling, the gasoline input has to be related to the gasoline storage, only. The model for the PEV energy hub can therefore be rewritten as

$$L(t_{op}) = \mathcal{E}(\Xi) \left( C\left(L(t_{op})\right) - S\left(L(t_{op})\right) \right) \left( \frac{P(t_{op})}{\dot{E}(t_{op})} \right),$$

(4.14)

with
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\[ \mathbf{C}(L(t_{\text{op}})) = \begin{pmatrix} c_{\text{el k in D}}(L(t_{\text{op}})) & c_{\text{gaso k in D}}(L(t_{\text{op}})) & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}, \quad (4.14a) \]

\[ \mathbf{S}(L(t_{\text{op}})) = \begin{pmatrix} \frac{c_{\text{el k in D}}(L(t_{\text{op}}))}{\eta_{\text{el}}} & \frac{c_{\text{gaso k in D}}(L(t_{\text{op}}))}{\eta_{\text{gaso}}} \\ \frac{1}{\eta_{\text{el}}} & 0 \\ \frac{1}{\eta_{\text{el}}} & 0 \\ \frac{1}{\eta_{\text{el}}} & 0 \\ 0 & \frac{1}{\eta_{\text{gaso}}} \end{pmatrix}, \quad (4.14b) \]

and

\[ \mathbf{P}(t_{\text{op}}) = \begin{pmatrix} P_{\text{el}}(t_{\text{op}}) \\ P_{\text{gaso}}(t_{\text{op}}) \\ P_{\text{dis}}(t_{\text{op}}) \end{pmatrix}, \quad \dot{\mathbf{E}}(t_{\text{op}}) = \begin{pmatrix} \dot{E}_{\text{el}}(t_{\text{op}}) \\ \dot{E}_{\text{gaso}}(t_{\text{op}}) \end{pmatrix}. \quad (4.14c) \]

### 4.2.1 The single step PEV energy hub model

The PEV energy hub model can be used for the simulation of individual vehicles in different states. One application example of the model is to simulate driving behavior and the evolution of the onboard storage energy level. Results include the SOC of the battery at arrival for individual PEVs. The SOC of the battery at arrival is a crucial input to management of PEV demand.

In order to simulate the driving behavior, an optimization can be formulated minimizing

\[ \mathcal{F}^{\text{single}}(\dot{E}_{\text{el}}(t_{\text{op}}), \dot{E}_{\text{gaso}}(t_{\text{op}})) = P_{\text{el}}(t_{\text{op}}) \frac{\pi_{\text{el}}(t_{\text{op}})}{E_{\text{el}}(t_{\text{op}})} + P_{\text{gaso}}(t_{\text{op}}) \pi_{\text{gaso}}(t_{\text{op}}). \quad (4.15) \]

The function minimizes total energy expenditures for driving. The energy costs include costs for electricity \( \pi_{\text{el}}(t_{\text{op}}) \) and for gasoline \( \pi_{\text{gaso}}(t_{\text{op}}) \). The cost factors are time dependent as they could vary from one driving time step to another. The driving time step \( t_{\text{op}} \) is chosen to 1 s. The cost factor for electricity is multiplied by a penalization factor for battery discharging. This objective function models a PEV in a charge depleting driving strategy [106, 115]. When using this strategy, electricity is preferred for propulsion. This is modeled by setting the penalization factor
for electricity in (4.15) lower than the one for gasoline. The constant $\kappa$ in the battery discharge penalization factor is a tuning parameter and chosen such that the penalization factor for electricity usage becomes higher than the one for gasoline usage if the SOC of the battery is equal to 20%. Then, the PEV switches its driving strategy into a charge sustaining one [115]. The charge sustaining strategy uses both electricity and gasoline to propel the vehicle while keeping the energy level of the battery somewhat constant. The PEV model also includes the possibility to use a blended strategy when driving [115].

The model uses multiple steps to simulate driving behavior. However, only one time step at a time is considered in the optimization. This represents a realistic situation as the driving behavior is usually not known in advance.

The PEV energy hub optimization is subject to

$$L(t_{op}) = \mathcal{E}(\Xi) \left( C(L(t_{op})) - S(L(t_{op})) \right) \left( P(t_{op}) \overline{E}(t_{op}) \right), \quad (4.16a)$$

and

$$\begin{align*}
\ddot{E}_{\text{el}}^{\min} &\leq \ddot{E}_{\text{el}}(t_{op}) \leq \ddot{E}_{\text{el}}^{\max}, \quad (4.16b) \\
\dot{E}_{\text{el}}^{\min} &\leq \dot{E}_{\text{el}}(t_{op}) \leq \dot{E}_{\text{el}}^{\max}, \quad (4.16c) \\
\dot{E}_{\text{el}}^{\min} &\leq \dot{E}_{\text{el}}(t_{op}) \leq \dot{E}_{\text{el}}^{\max}, \quad (4.16d) \\
\dot{E}_{\text{gaso}}^{\min}(t_{op}) &\leq \dot{E}_{\text{gaso}}(t_{op}) \leq \dot{E}_{\text{gaso}}^{\max}, \quad (4.16e) \\
\dot{E}_{\text{gaso}}^{\min} &\leq \dot{E}_{\text{gaso}}(t_{op}) \leq \dot{E}_{\text{gaso}}^{\max}, \quad (4.16f) \\
\dot{E}_{\text{gaso}}^{\min} &\leq \dot{E}_{\text{gaso}}(t_{op}) \leq \dot{E}_{\text{gaso}}^{\max}, \quad (4.16g) \\
P_{\text{diss}}^{\min} &\leq P_{\text{diss}}(t_{op}) \leq P_{\text{diss}}^{\max}, \quad (4.16h)
\end{align*}$$

with

$$\begin{align*}
t_{\text{gaso}} &= 1 \quad \text{if} \quad \dot{E}_{\text{gaso}}(t_{op}) \geq 0 \land 0 \leq t_{\text{gaso}}^{\text{on}} \leq t_{\text{gaso}}^{\text{on, max}}, \quad (4.16i) \\
t_{\text{gaso}} &= 0 \quad \text{if} \quad \dot{E}_{\text{gaso}}(t_{op}) = 0 \land t_{\text{gaso}}^{\text{on}} > t_{\text{gaso}}^{\text{on, max}}, \quad (4.16j) \\
\dot{E}_{\text{gaso}}^{\min}(t_{op} + 1) &= \dot{E}_{\text{gaso}}(t_{op}). \quad (4.16k)
\end{align*}$$

The equality constraint (4.16a) is the energy hub equation of the PEV model. The constraint ensures that the kinetic load, which is needed for propulsion, is fully supplied by power from the onboard storages and converters. Constraint (4.16b)–(4.16d) are related to the battery and the electric motor in the PEV. The first constraint gives that the power derivative drawn from or fed into the battery is limited to its specified technical bounds. The second constraint limits the actual power drawn
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from the battery and fed into the motor. Then, (4.16d) ensures that the battery is not overcharged or excessively depleted. Constraint (4.16e) gives that the power derivative drawn from the combustion engine during acceleration is limited. Furthermore, (4.16f) ensures that the power drawn from the combustion engine is between an upper and a lower bound where the lower bound is determined by the driving situation. Constraint (4.16g) gives that the gasoline tank is operated between its physical lower and upper filling levels and (4.16h) allows power to be dissipated in a predefined range at each driving time step.

The engine is regarded as an auxiliary power source in the PEV and should not be utilized often. Its operation is controlled by a heuristic. The heuristic adjusts the range of the power output from the combustion engine dynamically while driving. The heuristic of the engine is formulated through the constraints (4.16i)–(4.16k). It limits the engine to a minimum running time $t_{on,max}^{gas}$ once it is switched on. The constraint ensures that the engine is not intermittently switched on and off which would make its operation inefficient and unrealistic.

Once the engine needs to be utilized, the minimum power output of the last optimization step ($t_{op}^{-1}$) is taken as the lower bound for the next optimization step. This is expressed by (4.16k). If the possibilities of using electricity are fully exploited and the combustion engine needs to be utilized while driving, the PEV switches from a charge depleting into a blended strategy, where the engine is utilized rather heavily, propelling the vehicle and also partly charging the battery.

The optimization formulation needs to be adjusted for different energy flows that can occur when driving. For example, in case of regenerative breaking, electricity flows from the motor, which then acts as a generator, into the battery. Depending on the energy flow within the PEV energy hub, the efficiencies of storages and converters have to be adjusted which then accounts for the different usage of the converters in the model. The different efficiencies of the power paths are summarized in Table 4.2 for the varying converter utilization situations.

During regenerative breaking, the power path of electricity is defined by the regenerative breaking efficiency from the motor, acting as a generator, into the battery. This value is different than for situations where the vehicle is accelerating. The combustion engine could also be switched on during a regenerative breaking situation. Then, the battery will also be charged by the combustion engine. A summary of the efficiency values
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<table>
<thead>
<tr>
<th>PEV driving case</th>
<th>coupling factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>driving:</td>
<td>$c_{el,kin,D} = \eta_{el,mot}\eta_{dc}$</td>
</tr>
<tr>
<td></td>
<td>$c_{gaso,kin,D} = \eta_{ICE}\eta_{gen}\eta_{el,mot}$</td>
</tr>
<tr>
<td>regenerative breaking:</td>
<td>$c_{el,kin,D} = \eta_{reg}$</td>
</tr>
<tr>
<td></td>
<td>$c_{gaso,kin,D} = \eta_{ICE}\eta_{gen}$</td>
</tr>
<tr>
<td>charging:</td>
<td>$c_{el,kin,D} = 1/\eta_{c}$</td>
</tr>
<tr>
<td></td>
<td>$c_{gaso,kin,D} = \eta_{ICE}\eta_{gen}$</td>
</tr>
</tbody>
</table>

Table 4.2: Coupling factors utilized in the PEV energy hub single step model.

used is given in Table A.1 which is found in the Appendix. They are, together with other PEV parameters of the model, partly assumed and partly taken from literature [115–120].

4.2.2 Simulations of the PEV single step model

In order to illustrate the function and flexibility of the PEV energy hub model, it is first used to simulate driving behavior. Then, a potential daily behavioral pattern including driving, charging and the provision of ancillary services is simulated.

Driving simulation

The first driving simulation is carried out for a composition of different drive cycles. The composition consists of the Urban Dynamic Drive Cycle (UDDS) with a total driven distance of 7.9 miles, of the Highway Fuel Economy Cycle (HWFET) with a total driven distance of 10.26 miles, of the New York City Cycle (NYCC) with a total driven distance of 1.18 miles and of the Federal Test Procedure (FTP) 75 with a total driven distance of 11.04 miles [112].

The simulation results are depicted in Fig. 4.2. The speed profile of the drive cycle composition is shown in Fig. 4.2(a) and incorporates a step size $t_{op}$ of 1 s. Figure 4.2(b) shows the demanded power derived from the speed profile. It is calculated using specific vehicle data and (4.11). The demanded kinetic power is supplied by the battery and the electric motor together with the ICE. The power profile, which is drawn from the battery when driving, is shown in Fig. 4.2(c). The profile of the ICE
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Figure 4.2: Simulation of various test driving cycles; see text.

(a) Vehicle Speed  (b) Kinetic Load
(c) Demanded Power from Battery  (d) Demanded Power from ICE
(e) SOC of Battery  (f) Gasoline Tank Level

is illustrated in Fig. 4.2(d). The storage level of the battery and of the gasoline tank are shown in Fig. 4.2(e) and Fig. 4.2(f), respectively.

Most of the power demanded for propulsion is supplied by the battery. Only during times when the power derivative exceeds the upper technical limit of the battery, the ICE is used to supply the rest. This can be observed during the NYCC part of the combined cycle. Here, much power is demanded from the ICE because the variations in the load are high from one time step to another and cannot be supplied by the battery. The minimum operation time for the ICE is set to 300 s in the utilized heuristic. During this time, the ICE supplies a part of the kinetic power demand while the rest of the generated power is fed back into the battery or is dissipated. This is an example for a blended strategy while driving. The utilization of the ICE also includes situations where the vehicle is either standing still or breaking. In both situations the battery is recharged through the ICE. Additionally, when breaking, recaptured power from the electric motor is also fed into the battery. After 300 s the ICE is switched off if no additional power is needed.
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The SOC decreases to 42.5% of the battery capacity after simulation of this drive cycle composition. Most of the electricity is consumed during the highway cycle as the ICE is never used, the overall power demand is highest in comparison to the other cycle parts and barely any energy is recaptured through regenerative breaking. A total distance of 29.93 miles is driven in this combined cycle. This gives a fuel economy of 75 miles per gallon (3.1 l/100 km) which is considerably less than found in other literature [115]. However, it should be noted that the battery constitutes a comparably high SOC at arrival. This indicates that the single step model, although featuring a preference for electricity, still uses a substantial amount of gasoline. About 0.12 kWh/km are consumed.

In order to show how the PEV energy hub model behaves once the battery is depleted, ten consecutive UDDS drive cycles are simulated. Figure 4.3 illustrates the results. It can be observed that after seven cycles (at around 8’000 s) the battery is depleted to 20% SOC and the model switches to a charge sustaining driving strategy. Subsequently, the SOC of the battery remains close to the minimum SOC. Using this strategy, the ICE supplies the power for propulsion of the vehicle.
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but also partly charges the battery as seen in Fig. 4.3(c), Fig. 4.3(d) and Fig. 4.3(e) at around 10'000 s. Then, the ICE power output is particularly high; see Fig. 4.3(d). This increases the SOC of the battery; see Fig. 4.3(e). However, in this situation the battery still supplies the net transient load as it offers the highest operational flexibility. The net power from the ICE and kinetic power demand is either supplied by or stored in the battery.

In total, ca. 79 miles are driven and ca. 1.5 gallons of gasoline are used. When analyzing the blended driving strategy of the PEV model, a fuel economy of 120 miles per gallon is found (1.96 l/100 km), which is similar to other publications using more advanced models. When comparing the result with other values given in literature, a 10 % deviation in battery utilization time can be found [115]. It should be noted that the period during which the ICE is mostly utilized for propulsion, i.e. the charge sustaining time period, is not taken into account when calculating the fuel efficiency. About 0.16 kWh/km are consumed.

Simulation of different PEV states

The flexibility of the PEV energy hub model and the effect of different PEV states, introduced in Chapter 3, is illustrated by simulating driving, uncontrolled charging and the provision of V2G services. The operating state decision function adjusts the coupling matrix according to the particular state of the PEV.

Figure 4.4 shows a possible daily PEV schedule. The schedule incorporates driving (green), charging (red) and V2G services (blue). The states are indicated by arrows in the figures for better visibility. As can be observed in Fig. 4.4(a), the simulated vehicle behavior starts with three UDDS drive cycles. Then, the vehicle offers ancillary services (here secondary control) through V2G. It quits the service in order to charge before departing and driving another four UDDS cycles. When the vehicle stops, it charges again. Obviously, when providing V2G or charging, the vehicle does not move and therefore its speed as well as the kinetic power demand are zero as shown in Fig. 4.4(b).

After the first driving period, the SOC decreases to about 60 %. Then, the provision of ancillary services starts. The ancillary service signal used for the simulation of the V2G mode is taken from the Swiss TSO
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Swissgrid\(^2\). The original signal is given in per unit (p.u.). Taking into account the connection capacity of a single PEV when providing V2G services, the regulation signal is multiplied by the single phase connection capacity of a PEV which is assumed to be 3.5 kW. The signal is shown in Fig. 4.4(c). It is positively biased and, in terms of power values, much smaller than the power which is drawn from the battery during driving periods. The signal is fed into the PEV energy hub model via \( P_{el}(t_{\text{op}}) \). Here, it is assumed that negative power values of the V2G regulation signal cause the vehicle to discharge and positive values to charge, respectively.

During the period in which the PEV is connected the regulation signal is mostly positive. Therefore, the PEV charges most of the time. However, the power with which the PEV charges varies according to the input signal. The evolution of the SOC can be observed in Fig. 4.4(e). The battery energy level increases. At some point, the vehicle leaves the V2G mode and transfers into the uncontrolled charging state. The PEV is then charged until the battery is full. After driving for some time, the vehicle is partly charged before leaving.

\(^2\)The signal utilized here is the same signal as in Chapter 3.3.
4.2.3 The multi period PEV energy hub model

The single step PEV energy hub model does not anticipate the future driving behavior. For this model, it was shown that, although the objective function in the single step model is designed such that the model prefers electricity, still substantial amounts of gasoline are used. In order to determine the maximum amount of electricity which can be used for propelling the vehicle, the single step PEV energy hub model can be modified. A multi period formulation allows to find a global minimum for total energy consumption costs when driving, i.e., it maximizes the utilization of electricity for propulsion. Such result can be used to create a worst case scenario for a power system. The energy demanded from the power system to supply a PEV fleet could be assessed through the multi period model whose results could be scaled up to represent a large electric vehicle fleet.

The multi period PEV energy hub model is formulated similarly to the single step model. The multi period model minimizes

$$F^{\text{multi}}(\dot{E}_{el}(t_{\text{op}}), \dot{E}_{gaso}(t_{\text{op}})) = \sum_{t_{\text{op}}=1}^{T_{\text{end}}}(P_{el}(t_{\text{op}})\pi_{el}(t_{\text{op}}) + P_{gaso}(t_{\text{op}})\pi_{gaso}(t_{\text{op}})),$$

which is the objective function and includes the total energy consumption costs for the complete drive cycle. Here, $T_{\text{end}}$ gives the maximum number of drive cycle time steps. It should be noted that the optimization approach assumes that the complete drive cycle is known before. This is somewhat unrealistic as the driver’s behavior, i.e., acceleration and breaking, cannot be know with certainty. The assumption of complete information allows to determine the maximum of electricity utilization.

The multi period optimization is subject to

$$L(t_{\text{op}}) = \mathcal{E}(\Xi) \left( \begin{array}{cc} C & -S \end{array} \right) \left( \begin{array}{c} P(t_{\text{op}}) \\ \dot{E}(t_{\text{op}}) \end{array} \right),$$

(4.18a)
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and

\[
\begin{align*}
\ddot{E}_{\text{min}}^{\text{el}} & \leq \ddot{E}_{\text{el}}(t_{\text{op}}) & \leq \ddot{E}_{\text{max}}^{\text{el}}, \\
\dot{E}_{\text{min}}^{\text{el}} & \leq \dot{E}_{\text{el}}(t_{\text{op}}) & \leq \dot{E}_{\text{max}}^{\text{el}}, \\
\dddot{E}_{\text{min}}^{\text{el}} & \leq \dddot{E}_{\text{el}}(t_{\text{op}}) & \leq \dddot{E}_{\text{max}}^{\text{el}}, \\
\ddot{E}_{\text{min}}^{\text{gaso}} & \leq \ddot{E}_{\text{gaso}}(t_{\text{op}}) & \leq \ddot{E}_{\text{max}}^{\text{gaso}}, \\
\dot{E}_{\text{min}}^{\text{gaso}} & \leq \dot{E}_{\text{gaso}}(t_{\text{op}}) & \leq \dot{E}_{\text{max}}^{\text{gaso}}, \\
\dddot{E}_{\text{min}}^{\text{gaso}} & \leq \dddot{E}_{\text{gaso}}(t_{\text{op}}) & \leq \dddot{E}_{\text{max}}^{\text{gaso}}, \\
P_{\text{min}}^{\text{diss}} & \leq P_{\text{diss}}(t_{\text{op}}) & \leq P_{\text{max}}^{\text{diss}}.
\end{align*}
\]  

Equation (4.18a) formulates the equality constraint of the optimization scheme. The constraint ensures that the kinetic load is supplied by the onboard storages. It should be noted that the coupling and the storage matrix in the multi period approach are not adjusted for the different power flow situations which can occur in the hub. This is done for complexity reasons\(^3\). The different converter efficiencies are approximated by average values and therefore the matrices are not load dependent as observed in (4.18a). The other constraints are left the same as in the single step hub model. The only difference is that no operation time constraint is imposed on the ICE. This is done for the same reason as avoiding the load dependent coupling and storage matrices.

4.2.4 Simulation of the PEV multi period model

The multi period model can be used to simulate various drive cycles. First, a drive cycle composed of two UDDS cycles is simulated. The results are illustrated in Fig. 4.5. Figure 4.5(a) shows the speed profile and Fig. 4.5(b) shows the demanded kinetic power for this profile. Fig. 4.5(c) depicts the power drawn from the battery and Fig. 4.5(d) shows the power supplied by the ICE. It can be observed that most of the power is supplied by the battery. The ICE is barely used. Only during a very short interval the ICE is in operation at almost its full power. During this time the battery is charged. The graph plotting the ICE power supply illustrates how the missing constraint on minimum ICE operation time affects its utilization. The ICE is scheduled for very short time intervals. Although this is rather unrealistic, it allows for maximum utilization of electricity for propulsion. Figure 4.5(e) and

\(^3\)Implementing a similar scheme as in the single step model would lead to a mixed integer linear problem (MILP). For large optimization vectors, such as the ones used here, the computational time would not be acceptable. Hence, this is avoided here.
Figure 4.5: Simulation of two Urban Dynamic Drive Cycles; see text.
(a) Vehicle Speed  (b) Kinetic Load
(c) Demanded Power from Battery  (d) Demanded Power from ICE
(e) SOC of Battery  (f) Gasoline Tank Level

Fig. 4.5(f) show the SOC of the battery and the content of the gasoline tank, respectively. Obviously, the SOC is decreasing when driving while the content of the gasoline tank barely changes. Only during times when the ICE is scheduled for high power outputs, the gasoline content decreases. This decrease is, however, very small and cannot be seen in Fig. 4.5(f).

Figure 4.6 shows the simulation results in case the PEV should be traveling far enough so that the battery is depleted until its minimum allowed SOC, assumed here to be 20%. Six UDDS drive cycles are simulated for the same PEV design used before for the single step model. Figure 4.6(a) and Fig. 4.6(b) show the speed and the power profile of the drive cycle composition. Figure 4.6(c) and Fig. 4.6(d) depict the power drawn from the battery and produced by the ICE. It can be observed that the ICE is barely scheduled during the first five UDDS cycles. Only, the battery is used to propel the vehicle. However, during the sixth cycle, the ICE is utilized. During this time, the ICE supplies most of the kinetic load. The battery is utilized only for the transient power needed. This can also be seen in Fig. 4.6(e) and Fig. 4.6(f) where the SOC of the battery
4.3 Sensitivity Analysis

In order to compare the performance of the single and the multi period model, a sensitivity analysis has been performed investigating the energy consumption. Both, the single and the multi period model are simulated using different driving cycles and varying vehicle weights. The results are depicted in Fig. 4.7 – Fig. 4.10. Figure 4.7(a) compares the electricity consumption of the single and the multi period model for the

is decreasing until 20% and is kept constant thereafter. Only little fluctuations can be seen. The energy level of the battery storage is inverse to the one from the gasoline tank. The latter stays rather constant until the battery is depleted. Then, the gasoline level in the tank starts to decrease. In this situation, the multi period PEV energy hub model is in charge sustaining mode.

4.3 Sensitivity Analysis of the Single Step and the Multi Period PEV Model

Figure 4.6: Simulation of ten Urban Dynamic Drive Cycles; see text.
(a) Vehicle Speed  (b) Kinetic Load
(c) Demanded Power from Battery  (d) Demanded Power from ICE
(e) SOC of Battery  (f) Gasoline Tank Level
Figure 4.7: Comparison of the models’ energy consumptions for the UDDS drive cycle.
(a) Electricity consumption of single step and multi period model.
(b) Gasoline consumption of single step and multi period model.

UDDS drive cycle while Fig. 4.7(b) compares the gasoline consumption for both models and different weights. The electricity consumption is given in kWh/km; the gasoline consumption is given in ml/km. Obviously, the multi period model utilizes substantially more electricity for propulsion than the single step model. With growing weight, the utilization of electricity grows for the multi period model but decreases for the single step approach. In general, the single step model utilizes more gasoline than the multi period model. With growing vehicle weight, the single step model uses more gasoline for propulsion while the gasoline consumption stays almost constant for the multi period model. The consumption values are fitted with a linear regression model in order to determine a simple law for the dependence of energy carrier consumption on the vehicle weight. The linear regression function equations are given in the plots, respectively.

Figure 4.8–Fig. 4.10 plot also energy consumption over vehicle weight but for differing drive cycles. In general, the multi period model prefers electricity and saves gasoline. The relation between energy consumption and weight for the different drive cycles are given in the plots, respectively. In the case of NYCC, consumption values for the vehicle weight of 1525 kg are missing. This is due to the formulation of the single step optimization. As the optimization is not able to anticipate future load, the setpoint of the converters is moved into a state, where, due to design limits on ramping capabilities of the converters, the problem
4.3. Sensitivity Analysis

Figure 4.8: Comparison of the models’ energy consumptions for the FTP drive cycle.
(a) Electricity consumption of single step and multi period model.
(b) Gasoline consumption of single step and multi period model.

Figure 4.9: Comparison of the models’ energy consumptions for the HWFET drive cycle.
(a) Electricity consumption of single step and multi period model.
(b) Gasoline consumption of single step and multi period model.
Figure 4.10: Comparison of the models’ energy consumptions for the NYCC drive cycle.

(a) Electricity consumption of single step and multi period model.
(b) Gasoline consumption of single step and multi period model.

can become infeasible. Such a situation appears for the vehicle weight of 1525 kg. It should be noted that this problem can be solved by redesigning the vehicle, i.e., using other vehicle parameters and converter limits. For consistency reasons, this has not been performed here.

4.4 Concluding Remarks

This chapter developed a model for individual PEVs. The model is able to calculate the energy consumption of the vehicle if specific driving cycles, i.e., driving patterns, are given as an input to the model. The advantage of actually having such a model at disposal is that the energy consumption of a large PEV fleet can be easily simulated by simulating individual vehicles driving behavior and performing an aggregation. The model for individual vehicles also allows to vary the fleet composition by changing PEV design parameters such as weight. Then, the electricity consumption for specific driving behaviors, e.g., suburban streets, city streets or highways, can easily be determined using regression functions. The resulting SOC of the individual cars of the fleet is a crucial input parameter for PEV demand management as will be explained in Chapter 6. The chapter will elaborate on a possible application of the developed PEV model. In summary, the model allows to calculate individual vehicle energy consumption and avoids to rely on assumptions of energy consumption values which vary widely in literature.
Chapter 5

Application of Agent Based Modeling for PEV Demand Management

This chapter develops a PEV demand management scheme using agent based modeling (ABM). The scheme is based on game theory and uses the concept of mechanism design, a subclass of game theory, to simplify the iterative nature of agent learning into an optimization. This is done by utilizing the so called revelation theorem. Once the optimization framework is designed, the concept of PEV Managers, a PEV demand management platform usable in electricity grids, is elaborated. Its functionality is shown in a simple four node example. Finally, the PEV Manager concept is extended to a hierarchical structure using a Supervisory PEV Manager, which controls several, underlying PEV Managers.

5.1 Introduction to the Concept of Mechanism Design

Game theory may be defined as the study of mathematical models which describe the interaction between rational, intelligent decision makers, often referred to as agents. The interaction may include cooperation and conflict. There are different classes of games including strategic form games.
A strategic form game $\Gamma$ is defined as a tuple $\langle N^P, (S_i)_{i \in N^P}, (u_i)_{i \in N^P} \rangle$ where $N^P = \{1, 2, \ldots, n^P\}$ is a finite number of players or agents with $S_1, S_2, \ldots, S_{n^P}$ which are the strategy sets of the players $1, \ldots, n^P$, respectively. Mappings $u_i : S_1 \times S_2 \times \ldots S_{n^P} \rightarrow \mathbb{R}$ for $i = 1, 2, \ldots, n^P$ are called utility functions. The set $S$ is the collection of all agents’ strategy profiles. It should be noted that the utility of an agent depends not only on its own strategy but also on the strategies of the rest of the agents in the game. Every profile of strategies induces its own outcome. A strategic form game is said to be finite if $N^P$ and all strategy sets $S_1, \ldots, S_{n^P}$ are finite [121]. The agents in such a strategic form game compete for an outcome based on their utility functions.

Key notions in strategic form games are:

1. Utility theory,
2. Rationality,
3. Intelligence,

Utility theory allows to express the preferences of agents in terms of payoffs which are in some utility scale. Utility theory is the science of assigning numbers to the outcomes of a game in a way which reflects the preferences of the participating agents. The theory is an important contribution of von Neumann and Morgenstern, who stated and proved the expected utility maximization theory. The theorem states that, for any rational decision maker, a way of assigning utility numbers to different outcomes must exist which gives that the decision maker would always choose the option that maximizes his expected utility [122].

Another key notion in game theory is that the agents are rational. An agent is understood to be rational if the agent makes decisions which represent his pursuit of its own objectives. It is assumed that each agent’s objective is to maximize the expected value of its own payoff measured in some utility scale. A key observation is that self-interest is essentially an implication of rationality. It should be noted that maximizing utility is not necessarily the same as maximizing expected monetary returns. The utility scale might differ from the monetary scale [121].

Intelligence connotes that each agent participating in the game knows everything about the game that a game theorist knows. The player
can make any inferences about the game which are also possible for a
game theorist. Hence, an intelligent agent behaves strategically if it fully
takes into account its own expectation of the behavior of other game
participants when determining its strategy [121].

The notion of common knowledge is an important implication of intel-
ligence. A fact is common knowledge among the playing agents if every
agent knows it, every agent knows that every agent knows it, and so
on [123]. If a fact is known to all agents, without the requirement of all
agents knowing that all agents know it, etc., then such a fact is called
mutual knowledge. An agent’s private information is any information
that the agent has and that is not common knowledge among all other
agents [121,123].

In strategic form games, agents will be able to play the game several
times and learn from the outcomes. Dependent on their experience, they
will adapt their behavior and and act differently, depending on common
knowledge, their intelligence, their utility and rationality. The goal of
mechanism design is to design a set of rules for which the game, e.g. an
auction, delivers constantly the same result. Within a properly designed
mechanism the agents reveal their private information and no strategic
behavior will be observed.

5.2 Using Mechanism Design for PEV Demand Management

The approach of a strategic form game can be used to describe PEV
agents that desire power/energy at a certain location in an electricity
network and compete for it in a game, i.e., in an auction. In order to
enable the possibility of an auction, the good for which the agents com-
pete, in this case power, must be limited. Typically, the power is not
a scarce good for consumers in electricity networks. However, assum-
ing a large number of charging PEV agents, and assuming also to use
the infrastructure which is in place nowadays, overloading of assets or
violation of the feasible voltage ranges could occur. In such cases, the
desired power of the PEV agents is higher than the power which can be
supplied. This would give rise to a competition for the available power
among the connected PEV agents.
The competition could be settled by an auction. Using the notation given in Chapter 5.1, the set of players or agents \( N^P \) in a strategic form game can be translated into a set of PEV agents

\[
v \in \mathcal{V}_n(T) = \{1, 2, \ldots, N^V_n(T)\}, \quad n \in \mathcal{N} = \{1, 2, \ldots, N\}.
\] (5.1)

They are competing for power during the time step \( T \). Here, \( N^V_n(T) \) denotes the total number of PEV agents connected in time step \( T \) to a node \( n \) of the electricity network. This number can vary from time step to time step as PEV agents arrive and/or leave. Furthermore, the PEV agents are assumed to act rational and intelligent.

### 5.2.1 The valuation parameter

The set of alternative outcomes from such an auction for scarce power is denoted \( \mathcal{O} \). The agents are required to make a collective choice from the set \( \mathcal{O} \). Prior to making the collective choice, each agent privately observes his preferences over the alternatives in \( \mathcal{O} \), i.e., the agent observes his preferences on the outcome of the auction. This is described by supposing that PEV agent \( v \) at node \( n \) privately observes a parameter which determines his preferences. The value of this parameter is not known to the other agents. The parameter is called valuation parameter or agent type. The rationale behind this parameter is that the individual valuation of power/energy differs from agent to agent. The valuation needs to rise if the amount of energy, which has to be charged in a certain time interval to achieve a desired battery SOC, is high. The parameter should also rise when the flexibility for charging decreases, i.e., less time is left to charge. The parameter is modeled by

\[
\theta_{v,n}(T) = 1 + \varrho \left( T / \left( \frac{t^\text{dep}_{v,n}}{\tau(T)} - \frac{soc^{\text{des}}_{v,n} - soc_{v,n}(T)}{\varpi(T)\eta_c} \right) \right)^h. \] (5.2)

The valuation parameter is dependent on the actual time step, \( T \), as well as the anticipated departure time, \( t^\text{dep}_{v,n} \), the desired state of charge at departure, \( soc^{\text{des}}_{v,n} \), the SOC at the actual time step, \( soc_{v,n}(T) \) and the chargeable energy in one time step expressed in SOC, \( \varpi(T)\eta_c \). The
parameters $\varrho$ and $h$ can be freely chosen to specify the behavior of the preference. The parameter $\tau(T)$ gives the length of time step $T$ in seconds. The definition of the valuation parameter is assumed to be the same for all agents in the game\(^1\).

The valuation parameter expresses the value of energy in the actual time step with respect to remaining charging opportunities. The valuation $\theta_{v,n}(T)$ is low when the SOC is high and close to the desired SOC, when the time to departure is long, or both. The value of $\theta_{v,n}(T)$ is high when the difference between the actual and desired SOC is high, the time to departure is relatively short, or both.

Figure 5.1 illustrates the evolution of one agent’s valuation parameter over time and for different exponents $h$. The agent is connected from $T = 1$ until $T = 60$. The PEV agent incorporates a SOC of 70 %. Therefore, it needs to charge from $T = 42$ on in order to attain its desired SOC. It can be observed that in case a PEV agent does not attain energy during the time it is parked, its valuation grows. In the case of $h = 2$ the behavior is more risk averse and the valuation grows earlier but slower. In the case of higher exponents $h$ the valuation grows later but faster. Then, the behavior is more aggressive in the end. Note that the value of $\theta_{v,n}(T)$ exceeds the maximum value of 5 after $T = 42$. Afterwards, the desired SOC cannot be attained until departure even

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\(^1\)This has not necessarily to be the case. One can also envision that different agents incorporate different functions which describe their personal behavior and their preferences. This is not implemented for the sake of simplicity.
when charging at full power. Typically, the value of $\theta_{v,n}(T)$ is then limited as indicated by the bold, red, horizontal line.

The variable $\Theta_{v,n}(T)$ denotes the set of private values of PEV agent $v, n$ in $V_n(T)$. The set of type profiles of all agents is given by $\Theta_n(T) = \Theta_{1,n}(T) \times \Theta_{2,n}(T) \times \ldots \times \Theta_{N_Y,n}(T)$. A typical strategy profile is represented as $\theta_n(T) = \theta_{1,n}(T), \theta_{2,n}(T), \ldots, \theta_{N_{Y,n},n}(T)$.

### 5.2.2 The benefit function

An agent specific value, which scores the outcomes $\mathcal{O}$ of the strategic game, has to be assigned to the agent. Following this rationale, one can think of the fact that a PEV agent has a certain benefit when having a certain energy level in its battery at its disposal. Intuitively, the benefit should be low when the battery is empty and it should be high when the battery is full. Further, the marginal benefit should decrease with higher battery energy levels or, in relative terms, with higher SOC. That is, the more energy is in the battery, the lower the increase in benefit should be. These latter characteristics of the PEV agent’s benefit can be achieved by defining a benefit function $b_{v,n}(soc_{v,n}(T), \tilde{q}_{v,n})$ according to

\[
b_{v,n}(soc_{v,n}(T), \tilde{q}_{v,n}) = \alpha_{v,n}(T) C^B_{v,n}(soc_{v,n}(T) - soc_{v,n}^{min} + \tilde{q}_{v,n}) - \beta_{v,n}(T) \frac{C^B_{v,n}(soc_{v,n}(T) - soc_{v,n}^{min} + \tilde{q}_{v,n})^2}{2}
\]

where $\tilde{q}_{v,n}$ is the acquired energy in per unit of battery capacity. Expressed differently, $\tilde{q}_{v,n}$ is the change in SOC in time step $T$. The parameters $\alpha_{v,n}(T)$ and $\beta_{v,n}(T)$ can generally be time dependent. However, in a first step, they are assumed to be constant and are calculated according to

\[
\alpha_{v,n}(T) = \pi_{max} = \pi_{gaso} \frac{\eta_{mot} \eta_{c} \eta_{dc}}{\eta_{CE}} \ [m.u] , \quad \beta_{v,n}(T) = \pi_{day.min} - \alpha_{v,n}(T) \frac{C^B_{v,n}}{2} \ [m.u].
\]

In (5.3), the parameter $C^B_{v,n}$ denotes the battery capacity of PEV agent $v, n$ while $\alpha_{v,n}(T)$ and $\beta_{v,n}(T)$ define the maximal marginal benefit and the slope of the marginal benefit. The parameters are expressed in
5.2. Mechanism Design for PEV Demand Management

monetary units \([m.u.]\). Thus, they could be related to electricity market prices. It appears realistic to set \(\alpha_{v,n}(T)\) to a value corresponding to the current gasoline price which is weighted by the efficiencies of the engine path in the hub model. This allows to include losses and to relate the gasoline consumption with the electricity consumption.

The value of \(\beta_{v,n}(T)\) specifies the sensitivity for attaining energy, i.e., the slope of the benefit function. Choosing a value or price at which the PEV should be charged to a certain SOC allows to determine \(\beta_{v,n}(T)\). Another way to define this parameter could be to use the lowest forecasted electricity price of the next day, \(\pi_{\text{day,min}}\), and set \(\beta_{v,n}(T)\) to a value at which the PEV agent will still want to charge when its SOC is at 100 %. Obviously, \(\beta_{v,n}(T)\) is a tuning parameter.

In order to express (5.3) in a more condensed form, it is rewritten as

\[
b_{v,n}(T, \Omega_{v,n}(T)) = \alpha_{v,n}(T)C_{v,n}^{B}(\Omega_{v,n}(T)) - \beta_{v,n}(T)C_{v,n}^{B}(\Omega_{v,n}(T))^2
\]

with

\[
\Omega_{v,n}(T) = \text{soc}_{v,n}(T) - \text{soc}_{v,n}^{\text{min}} + \tilde{q}_{v,n}.
\]

Figure 5.2 depicts the benefit function (5.5) as a function of SOC for one PEV agent. Two graphs are displayed. They show the evolution of the benefit function for battery sizes of 10 kWh and 20 kWh. The ordinate gives the value of the benefit function in monetary units (m.u.). Using the parameters \(\alpha_{v,n}(T) = 42.8 \text{ [m.u]}, \beta_{v,n}(T) = 21.175 \text{ [m.u]}\) and \(\text{soc}_{v,n}^{\text{min}} = 0.2\). It can be seen that the function is a parabola. The benefit grows faster for larger battery sizes. The function is bounded between SOC values of 20 % and 100 %. They represent the physical limits for the energy level in the battery and are indicated through the dotted, red, vertical lines. The function is strictly monotonically increasing and differentiable in the SOC interval.

5.2.3 The utility function

The individual PEV agent preferences over the game outcomes in time step \(T\) are expressed through an utility function \(u_{v,n}(T) : \mathcal{O}(T) \times \Theta_{v,n}(T) \to \mathbb{R}\) which incorporates the benefit function \(b_{v,n}(T, \Omega_{v,n}(T))\).

Given a certain outcome of the game \(o(T) \in \mathcal{O}(T)\) and \(\theta_{v,n}(T) \in \Theta_{v,n}(T)\), the value \(u_{v,n}(o(T), \theta_{v,n}(T))\) denotes the payoff that agent
v at node n with a valuation of $\theta_{v,n}(T) \in \Theta_{v,n}(T)$ receives from the final decision $o(T) \in O(T)$. In the more general case, $u_{v,n}(\cdot)$ depends not only on the outcome and the valuation parameter of agent v at node n, but also depends on the valuation parameters of the other agents at the particular node. This is expressed as $u_{v,n}(T) : O(T) \times \Theta_n(T) \rightarrow \mathbb{R}$.

For the strategic game which can be set up at each electricity node, the set of outcomes $O(T)$, the set of players $N_n^V(T)$, the valuation sets $\Theta_{v,n}(T)$ and the payoff functions $u_{v,n}(T)$, both with $v = 1, \ldots N_n^V(T)$, are assumed to be common knowledge among all the players. The specific value $\theta_{v,n}(T)$ observed by agent v is private information.

Now, the utility function of the PEV agent is defined as

$$u_{v,n}\left(q_{v,n}(T), soc_{v,n}(T), soc_{v,n}^{min}, \pi_n(T), \theta_{v,n}(T)\right) =$$

$$\theta_{v,n}(T) \left[ \alpha_{v,n}(T) C_{v,n}^B \left( soc_{v,n}(T) - soc_{v,n}^{min} + q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \right) \right.$$

$$\left. - \beta_{v,n}(T) C_{v,n}^B \left( soc_{v,n}(T) - soc_{v,n}^{min} + q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \right)^2 \right]$$

$$- \pi_n \left(T, \Theta_n(T)\right) C_{v,n}^B q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)).$$

(5.7)

In the utility function, the benefit function of the PEV agent is multiplied by its individual valuation parameter. From this value the product of a price signal $\pi_n\left(T, \Theta_n(T)\right)$, announced for this time step, and
5.2. Mechanism Design for PEV Demand Management

energy \( q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \), assigned to the agent, is subtracted.

The price \( \pi_n(T, \Theta_n(T)) \) can first be exogenously given, e.g., based on a real time energy price signal, but can deviate from this value depending on the outcome of the game, i.e., auction. Then, the price is endogenously determined by the outcome of the game. The variable \( q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \) is the energy amount attained in time step \( T \).

The amount is weighted by the individual battery capacity. The attained energy amount is dependent on the auction outcome, hence, on the personal energy valuation \( \theta_{v,n}(T) \) and the valuation profile \( \Theta_n(T) \) in this time step at the congested electricity node. The variable \( q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \) is given by

\[
q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) = \frac{S_r}{\varsigma(T)C_{v,n}} p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) ,
\]

\[
\Leftrightarrow q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) = \frac{1}{\varsigma(T)C_{v,n}} p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) ,
\]

with

\[
\varsigma(T) = \frac{3600\text{[s/h]}}{\tau(T)[s]} .
\]

Here, \( S_r \) denotes the reference electrical power for the base, \( p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \) is the rated power and \( p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \) is the power assigned to the PEV. The assigned power depends on the personal valuation parameter and at the same time on the distribution \( \Theta_n(T) \) of all other valuation parameters of PEV agents connected at the same node. Furthermore, \( \varsigma(T) \) is the relation between time step length in seconds and one hour. As \( \tau(T) \) is chosen to be 900s, \( \varsigma(T) \) is 4.

The utility function can be rewritten in a condensed form as

\[
u_{v,n}(T, \Omega_{v,n}(T), \pi_n(T), \theta_{v,n}(T)) = \theta_{v,n}(T)b_{v,n}(T, \Omega_{v,n}(T)) - \pi_n(T)C_{v,n}^B \tilde{q}_{v,n}
\]

now with

\[
\tilde{q}_{v,n} = q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) = \frac{p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T))}{\varsigma(T)C_{v,n}^B} .
\]

Figure 5.3 visualizes the utility function for one PEV agent. The agent is assumed to connect at time step \( T = 1 \) and to leave in \( T = 61 \). Fur-
thermore, it is assumed that, in each time step, no energy is assigned to the PEV agent. Figure 5.3 illustrates how the product of the valuation parameter and the benefit function evolves over time and over the battery energy level. The plot assumes a constant, exogenous price signal $\pi_n(T)$. The rated, constant price signal is set to 33 m.u./kWh which gives 660 m.u. for a 20 kWh battery and is indicated by the horizontal plane in the figure.

It can be observed that using this price signal, a PEV agent chooses to charge, i.e., competes for power, when its SOC is smaller than 40% in time step $T = 1$. In this case, the weighted marginal benefit is higher than the exogenous price signal. However, with time passing, the marginal benefit is weighted with a growing valuation parameter. Thus, a PEV agent which incorporates a SOC higher than 40% then also wants to compete for power in order to start charging. With less temporal flexibility in charging, i.e., with less parking time left, a PEV agent incorporating an even higher battery energy level joins this competition and so forth.

As an exemplification of the described behavior, the specific case of one specific PEV agent is emphasized by the solid line in Fig. 5.3. The case represents a PEV agent which incorporates an SOC of 70%. It can be observed that in the beginning the agent does not compete for power because its utility is negative, i.e., the value of the weighted marginal benefit is lower than the exogenous price signal. With less temporal
charging flexibility, the value of the weighted marginal benefit grows as indicated by the bold, vertical, black arrow in the figure. At \( T = 20 \) the weighted marginal benefit is bigger than the exogenous price signal. Here, the PEV agent starts to compete for power in order to charge. Recall that no energy is assigned to the agent during all time steps. Thus, the weighted marginal benefit increases until it reaches the maximum value, set here to \( \alpha_{v,n}(T) \).

Figure 5.4 shows the same situation but in two dimensions. This figure underlines how with less parking time available to charge the weighted marginal benefit grows. The increase in valuation causes the weighted marginal benefit to be higher than the exogenous price signal \( \pi_n(T) \) in \( T = 20 \). From this time, the PEV agent would like to start charging as the value of its utility becomes positive, i.e., the weighted marginal benefit is higher than the exogenous price signal.

5.3 Developing the PEV Manager

As derived in Appendix B, incentive rationality can be proven and incentive compatibility can be assumed to hold for the utility function, i.e., the constructed mechanism. Therefore, the revelation theorem holds and the mechanism becomes a direct mechanism [121]. Thus, every agent will announce its personal valuation parameter always truthfully. Using the

\[
\pi_n(T)
\]
revelation theorem, an optimization can be formulated which models the bidding behavior and which can be solved analytically. The optimization is assumed to be solved by a platform which is called the PEV Manager. The PEV Manager objective is formulated as

$$\max \sum_{v=1}^{N_n^V(T)} u_{v,n}(T, \Omega_{v,n}(T), \pi_n(T), \theta_{v,n}(T))$$

with

$$\Omega_{v,n}(T) = soc_{v,n}(T) - soc_{v,n}^{\min} + q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T))$$

The objective can be written out using (5.8) as

$$\max \sum_{v=1}^{N_n^V(T)} \theta_{v,n}(T) \cdot \left[ \alpha_{v,n}(T)C_{v,n}^{B} \left( soc_{v,n}(T) - soc_{v,n}^{\min} + \frac{1}{\zeta(T)C_{v,n}^{B}} p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \right) \right.$$  

$$- \beta_{v,n}(T)C_{v,n}^{B} \left( soc_{v,n}(T) - soc_{v,n}^{\min} + \frac{1}{\zeta(T)C_{v,n}^{B}} p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \right)^2 \right]$$

$$- \pi_n(T, \Theta_n(T))C_{v,n}^{B} \frac{1}{\zeta(T)C_{v,n}^{B}} p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T))$$

in order to show the individual parts of the objective function. The PEV Manager optimization is subject to

$$p_{v,n}^{\min}(T) \leq p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \leq p_{v,n}^{\max}(T)$$

$$soc_{v,n}^{\min} \leq soc_{v,n}(T) \leq soc_{v,n}^{\max}$$

$$P_n^{\min}(T) \leq \sum_{v=1}^{N_n^V} p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \leq P_n^{\max}(T)$$

The constraint (5.15a) includes limits on the maximum and minimum power which can be assigned to the PEV. The limits are imposed by the physical connection capacity of the PEV. Typical physical limits are
5.3. Developing the PEV Manager

Figure 5.5: Determination of the endogenous nodal control price signal.

3.5 kW for a single phase connection (16 A, 220 V), or 11 kW for a three phase connection. Constraint (5.15b) ensures that the battery cannot be overcharged or overly depleted. Typically, 20% of SOC is assumed as the lowest battery energy level. The last constraint, (5.15c), gives that the sum of all scheduled charging powers is lower than a maximum power \( P_{\text{max}}(T) \) which can be drawn from this node of the system. The maximum power is either determined by the transformer rating, feasible voltage bounds or the system of electricity lines feeding this node.

The optimization problem can be solved by using techniques described in [124–126]. When solving such a problem, a Lagrangian function can be set up using the objective function and the constraints. The Lagrangian function of this problem is given by (C.1) in Appendix C. Subsequently, the Karush-Kuhn-Tucker (KKT) constraints can be derived. They are formulated in (C.2a)-(C.2m) and are also found Appendix C. Solving the KKT-equations allows to determine a nodal control price signal. It can be derived from the KKT constraint (C.2a). The derivation itself is given in (C.3) in Appendix C. The nodal control price signal is finally determined as

\[
\pi_n(T, \Theta_n(T)) = \pi_n(T) + \frac{\zeta(T)}{1}[\sigma_{n, \text{upp}}(T) - \sigma_{n, \text{low}}(T)].
\]  
(5.16)
In (5.16), the endogenously determined nodal control price signal $\pi_n(T, \Theta_n(T))$ is derived from the exogenously given price $\pi_n(T)$ and a weighted markup which consists of the Lagrangian multiplier from constraint (5.15c). This constraint associates the individual charging setpoints to the temporal and spatial availability of power to be supplied to the fleet.

The derivation of the endogenously determined nodal control price signal is visualized in Fig. 5.5. The x-axis plots the power supplied to the cars connected in the area which the PEV Manager supervises. The maximum power which can be supplied to this fleet is illustrated by the vertical solid line and indicated by $P_n^{\text{max}}(T)$. The sum of the weighted marginal benefits, plotted on the y-axis, is shown through the solid, black line. As can be seen, the total demand exceeds the maximum available power. The latter is indicated by the black, vertical line. The intersection of the solid black line and the vertical line determine the nodal control price signal based on the following argumentation.

The scarcity of power gives rise to two, potentially nonzero Lagrangian multipliers denoted $\sigma^{\text{upp}}_{v,n}(T)$ for the violation of the upper power bound and $\sigma^{\text{low}}_{v,n}(T)$ for the lower bound. As the lower bound is usually not violated, the respective Lagrangian multiplier stays zero. However, the Lagrangian multiplier for the upper constraint can become nonzero and therefore adds a markup on the exogenously given price signal $\pi_n(T)$. Thus, in a congested situation, this becomes the new, endogenously determined control price signal. It can also be found by taking a particular utility function value at its specific charging setpoint and adding the value of the Lagrangian multipliers which relate to the individual power constraint.

## 5.4 Developing a Predictive PEV Manager

Generally speaking, the PEV Manager is able to reduce PEV load in order to avoid network stress. The PEV Manager considers the future by taking account of the agent’s desired SOC at an anticipated departure time (being actually in the future). The desired battery energy level is incorporated in the personal valuation parameter. However, the PEV Manager does not take into account that the network state can change
5.4. Developing a Predictive PEV Manager

in the future due to different base load situations or to the arrival of more PEVs. This could subsequently lead to a higher congestion of the area or a higher nodal price signal\(^2\).

A predictive version of the PEV Manager can take forecasts on base load as well as on potentially arriving PEVs into account. Such a predictive PEV Manager allows to distribute the power, available in different time steps, to a changing fleet of connected PEVs. In order to derive such a predictive PEV Manager, the PEV Manager formulation derived in (5.3) is extended in the following using a multi period receding horizon optimization, i.e., the optimization is performed for several time steps at once. The length of the receding horizon is denoted \(\Delta T^{RH}_n\) and comprises multiple time steps. The length can vary from one PEV Manager to another. The objective of the predictive PEV Manager is formulated to

\[
\max \sum_{t=T}^{T+\Delta T^{RH}_n} \sum_{v=1}^{N^V(t)} u_{v,n}(t, \Omega, \theta_{v,n}(t)) \quad (5.17)
\]

which can be written out to

\[
\max \sum_{t=T}^{T+\Delta T^{RH}_n} \sum_{v=1}^{N^V(t)} \theta_{v,n}(t). \\
\left[\alpha_{v,n}(t)C^{B}_{v,n}\left(\text{soc}_{v,n}(t) - \text{soc}_{v,n}^{\min} + \frac{1}{\zeta(t)C^{B}_{v,n}}\rho_{v,n}\left(t, \theta_{v,n}(t)\mid \Theta_n(t)\right)\right)\right. \\
- \beta_{v,n}(t)C^{B}_{v,n}\left(\text{soc}_{v,n}(t) - \text{soc}_{v,n}^{\min} + \frac{1}{\zeta(t)C^{B}_{v,n}}\rho_{v,n}\left(t, \theta_{v,n}(t)\mid \Theta_n(t)\right)\right)^2] \\
- \pi_n(t)C^{B}_{v,n}\frac{1}{\zeta(t)C^{B}_{v,n}}\rho_{v,n}\left(t, \theta_{v,n}(t)\mid \Theta_n(t)\right),
\]

\[(5.18)\]

\(^2\)If the manager would know this information, it would schedule the charging of the PEVs differently. PEVs, whose utility would not justify charging in the actual time step, could still be scheduled for being charged because their contribution to the multi period utility maximization would be higher (or the loss of utility smaller). This is due to the fact that the cars will still not be able to charge in the upcoming time steps because of a higher congestion by additional cars.
and which is subject to constraints formulated according to

\[ p_{v,n}^{\text{min}}(t) \leq p_{v,n}(t,\theta_{v,n}(t)|\Theta_n(t)) \leq p_{v,n}^{\text{max}}(t) \, , \quad (5.19a) \]

\[ \text{soc}_{v,n}^{\text{min}} \leq \text{soc}_{v,n}(t) + \sum_{t=T}^{T+\Upsilon} p_{v,n}(t,\theta_{v,n}(t)|\Theta_n(t)) \leq \text{soc}_{v,n}^{\text{max}} \, , \quad (5.19b) \]

\[ P_n^{\text{min}}(t) \leq \sum_{v=1}^{N_n(t)} p_{v,n}(t,\theta_{v,n}(t)|\Theta_n(t)) \leq P_n^{\text{max}}(t) \, , \quad (5.19c) \]

\[ \forall \Upsilon \in \{1,2\ldots \Delta T_{RH}^n\} \land \forall v \in V_n(t) \]

The predictive PEV Manager incorporates similar constraints as the single period PEV Manager. In (5.19a) the power allocated to an individual vehicle is limited to its physical capacity in each time step \( t \) of the optimization horizon. Constraint (5.19b) ensures that the battery of a PEV agent is not overcharged or depleted in each time step of the optimization horizon. Finally, (5.19c) gives that the power, which maximally can be supplied by the network in each time step of the receding horizon, is not violated by the imposed PEV demand. The Lagrangian function and the KKT constraints are given in (D.1) and (D.2a)–(D.2ak) found in Appendix D.

### 5.5 Example for the Integration of PEV Managers in Power Systems

The following example shows how PEV Managers can be utilized to avoid network stress. Figure 5.6 illustrates an electricity network subject to large scale PEV utilization. In Fig. 5.6 a medium voltage network, depicted by the grey lines, interconnects four different areas which incorporate business, industrial and residential load behavior. The behavior is modeled by using appropriate load curves. Transformers installed at the nodes supply the lower network levels, feeding the different urban areas illustrated by the radial networks. For simplicity, these networks are not modeled in this example. The PEVs are assumed to connect at the lower voltage level.

Each area fed by a transformer station is supervised by a PEV Manager. The manager uses a single period optimization as described in Section 5.3. The power flow in the medium voltage network is computed by the
5.5. Application Example of PEV Managers

Figure 5.6: Test network utilized to exemplify the application of PEV Managers in electricity networks. The test network features 4 interconnected nodes which incorporate a transformer, feeding the a lower voltage network, and a PEV Manager, respectively. The nodes represent different urban areas. The PEV Managers are controlled by a network operator. The operator is able to take command of the PEV Managers and their demand flexibility if congestion occurs. This is done via the PEV aggregator. In case problems occur, the operator sends load reduction requests to the PEV aggregator, which, here, always fulfills the request. This is in accordance with the elaborations found in Chapter 2. For the sake of simplicity, this indirect command is indicated by the blue, dash-dotted lines and the blue arrows.

The node which supplies the industrial area is used as a slack node. There, power is fed into the medium voltage network to supply the load. No generators are considered in this example. The generators are assumed to be connected on higher network levels. The power flow in the base case, meaning without any PEV demand management, is computed assuming that total energy costs should be minimized while supplying the total demanded power at each node. The energy costs are assumed to be constant.

When activating the PEV demand management, the optimal power flow is computed through the network operator by solving an optimization problem and minimizing
\[
\sum_{n=1}^{N} \zeta(T) \left( \pi_n(T) P_n(T) + \xi \left( L_{n,\text{PEV}}(T) - L_{n,\text{PEV,act}}(T) \right) \right), \quad (5.20)
\]

subject to

\[
L_n(T) = L_{n,\text{base}}(T) + L_{n,\text{PEV,act}}(T) \quad \forall n \in \mathcal{N}, \quad (5.21a)
\]

\[
L_n(T) - \eta_n \text{trafo} P_n(T) = 0 \quad \forall n \in \mathcal{N}, \quad (5.21b)
\]

\[
G(P_n(T)) = 0 \quad \forall n \in \mathcal{N}, \quad (5.21c)
\]

and

\[
P_{n,\text{min}} \leq P_n(T) \leq P_{n,\text{max}} \quad \forall n \in \mathcal{N}, \quad (5.22a)
\]

\[
P_{l,\text{min}} \leq P_l(T) \leq P_{l,\text{max}} \quad \forall l \in \mathcal{L}, \quad (5.22b)
\]

\[
U_{n,\text{min}} \leq U_n(T) \leq U_{n,\text{max}} \quad \forall n \in \mathcal{N}, \quad (5.22c)
\]

\[
0 \leq L_{n,\text{PEV,act}}(T) \leq L_{n,\text{PEV}}(T) \quad \forall n \in \mathcal{N}, \quad (5.22d)
\]

\[
\phi_n = 0 \quad n = 1. \quad (5.22e)
\]

The objective function, given by (5.20), incorporates the cost of the totally consumed energy in the first summand. The PEV load, imposed on the network by the PEV Managers, is considered as a flexible load in contrary to the base load of the system. In case of system overloading, the flexible PEV load can be curtailed and postponed. The postponement is performed by the network operator utilizing the PEV Managers. The latter take advantage of the charging flexibility of the PEVs connected to the particular PEV Managers.

The second term in the objective function penalizes the deviation of the load \( L_{n,\text{PEV,act}}(T) \), which is actually supplied, from the desired load \( L_{n,\text{PEV}}(T) \) of the particular PEV Manager. The parameter \( \xi \) is a penalization factor set to a high value to avoid excessive PEV shedding. The network operator faces a penalty when activating the PEV Managers.

Equation (5.21a) determines the total load at each node and (5.21b) ensures that the power supplied by the transformers, whose efficiency is given by \( \eta_n \), corresponds to the total load at the node. Equation (5.21c) gives that Kirchhoff’s law is obeyed.

The constraint (5.22a) gives that the power input, i.e., the power which is fed through the transformer at each node, is limited. The electric line limits are expressed through (5.22b) while (5.22c) ensures proper
5.5. Application Example of PEV Managers

voltage levels and (5.22d) gives the potential for curtailing the PEV load at each node. Finally, (5.22e) sets the reference angle in order to compute the power flow.

The system depicted in Fig. 5.6 is simulated for three different cases in order to show the functionality of the PEV Managers:

**Case 1: No PEV Demand Management:**

All PEV instantaneously start to charge at arrival until they are fully recharged.

**Case 2: PEV Managers avoid transformer overloading only:**

PEV demand management is active and avoids transformer overloading. No attention is given to line overloading or voltages.

**Case 3: PEV Managers avoid network congestion:**

PEV demand management is active and includes the possibility to postpone charging of PEVs in order to keep line loadings and voltage levels in sufficient ranges.

The behavior of the PEVs is determined by an agent based transportation simulation which will be explained in detail in the next Chapter. The PEVs incorporate behavioral patterns such as staying at home, going to work, education, shopping or leisure. One part of the fleet switches nodes in order to perform the activities. It is important to note that the network as well as the transportation behavior is used here as a generic example. No attention has been paid to the detailed assignment of home locations to the specific nodes.

The simulation results are shown in Fig. 5.7 and in Fig. 5.8, which illustrate the loading of the transformers and the loading of the lines in the system for the three different cases. Figure 5.7(a) shows the load of the four transformers for Case 1 when PEV demand is not managed. The dotted, red, horizontal lines indicate the thermal limits of the transformers. The thermal limit of transformer 1 is violated during the morning hours when agents using PEVs arrive at their work locations. Similarly, the thermal limit of transformer 2 is violated during morning as well as during afternoon hours. The thermal limits of transformer 3 and transformer 4 are violated during the morning hours and during the early evening hours. These are the times when the agents arrive at work or at home after performing their work activity.
Figure 5.7: Comparison of transformer loading including different PEV demand management schemes. They incorporate no management, the physical transformer limitations and transformer as well as line power limitations.
5.5. Application Example of PEV Managers

Figure 5.8: Comparison of line loading including different PEV demand management schemes. They incorporate no management, the physical transformer limitations and transformer as well as line power limitations.
Figure 5.8(a) shows the line loadings for Case 1. The maximum line ratings are indicated by the horizontal, red, dotted lines. It can be seen that during some time of the day, three lines are overloaded. In particular, Line $1 \rightarrow 2$ faces overload of up to 10 MW during the morning. This, together with the severe overloading of the transformers, is a situation which would be unacceptable from an operational and a security perspective.

As a typical application example, Fig. 5.7(b) shows the load situation when the PEV demand is managed at the different transformers, i.e., Case 2. The goal of the demand management here is to keep the loading of the transformers within the allowed region and avoid overload. It can be seen that no thermal transformer limits are violated anymore. The load of the transformers always stays within the allowed region. However, the load shape in the different areas differs from the one observed in Fig. 5.7(a). Much of the excessive load seen before is distributed over the day and to later hours where the transformer loading was not excessively high. Load valleys are filled up. Load peaks, as in Fig. 5.7(a), are not seen with active PEV demand management. They are mitigated and load plateaus appear.

Figure 5.8(b) shows the line loading for Case 2. The loading of the lines is substantially reduced in comparison to Case 1. Now, the loading incorporates plateaus where in the former case peaks have been seen. However, some lines still face excessive currents although load is rescheduled to other time steps. Obviously, the PEV management on the transformer level does not ensure that other operational bounds are satisfied.

Figure 5.7(c) shows the load of the four transformers for Case 3. Here, the operator takes full command of the PEV charging flexibility. The PEV demand is managed, i.e., rescheduled, in order to keep the loading of the transformers and the loading of the lines within the allowed operational limits. Figure 5.8(c) shows the line loadings for Case 3. No line limit is violated here. Overall, more PEV load than in Case 2 is shifted to later times or is even completely shed. The plateaus of the load curve illustrated in Fig. 5.7(c) are reduced in their height. This is done to avoid the overloading of the electricity lines and can be observed by crosschecking Fig. 5.7(c) and Fig. 5.7(b) as well as Fig. 5.8(c) and Fig. 5.8(b).
Taking full command of the PEV Managers ensures that the transformers are not overloaded. Then, the OPF is computed by the network operator making full use of the flexibility provided by the PEV Managers. The overloading of a line is avoided by the optimization through changing the load setpoints determined by the PEV Managers in the first step and postponing the charging of some PEVs. Although this introduces additional costs, which are included in the objective function, the alteration of the PEV Manager load setpoint ensures a power flow which avoids the violation of physical network limitations.

5.6 Developing a Supervisory PEV Manager

As the example in the last section suggests, most problematic network situations due to large scale PEV charging can be avoided by using PEV Managers. However, the electricity network incorporates several voltage levels. The mitigation of local problems on one level does not necessarily avoid problems on the next higher network level. In order to visualize the challenge, Fig. 5.9 gives an example of what possibly could happen in electricity networks.

The right hand side of Fig. 5.9(a) illustrates an urban area which is supplied by a radial electricity network. It is assumed that the voltage level of this network is 11/22 kV. Each node in the radial network represents a transformer station which feeds an underlying 400 V network. These transformer stations are equipped with a PEV Manager. The managers ensure that the radial network and the underlying 400 V network is in a secure state. This is illustrated by the green color of the PEV Manager screen.

The radial network is fed by a transformer connecting the lower voltage network to the 150 kV network. In certain cases, the 150 kV transformer can be overloaded due to the load situation on the underlying network level. The overload is indicated in Fig. 5.9(a) by the red color of the transformer. The overload of this transformer or its feeding lines needs to by mitigated. This is not possible with the so far presented scheme.
Figure 5.9: (a) Zone consisting of a radial 11/22 kV network and fed by a 150 kV tap changing transformer. PEV Managers at each node control the PEVs connected to the 11/22 kV transformer. Overloading of the 150 kV transformer is not necessarily avoided.

(b) Supervisory PEV Manager (S-PEV Manager) controls the PEV Managers on the 11/22 kV level. S-PEV Manager avoids the overloading of the 150 kV transformer by changing the load of each PEV Manager as indicated by the yellow screens.
Figure 5.9(b) illustrates a solution to this shortcoming. Installing a Supervisory PEV Manager (S-PEV Manager) at the next higher level, i.e., at the 150 kV transformer, allows to adjust the load imposed by the PEV Managers which are active only on the lower 11/22 kV level. This subsequently allows to mitigate overloads on the 150 kV level and voltage violations in the 11/22 kV network\(^3\). The S-PEV Manager thus clusters the PEV Managers at nodes \(n_z\) of its zone \(z\) under supervision. The term zone refers to the area which is fed by the radial network and which is not interconnected with other radial networks. Hence, a zone is defined as

\[
N_z \in \mathcal{N}_z \quad = \{1, ..., N_{\text{zone}}^z\} \quad , \\
\text{and} \quad z \in \mathcal{Z} \quad = \{1, ..., Z\} \quad , \\
\text{and} \quad \mathcal{N}_z \subset \mathcal{N} \quad .
\] 

In Fig. 5.9(b) the S-PEV Manager avoids the overloading of the 150 kV transformer by changing the setpoints of the underlying PEV Managers in his zone \(z\). The new charging setpoints differ from the setpoints calculated before by the individual PEV Managers. These setpoints are indicated in green in Fig. 5.9(a). The new setpoints, determined by the S-PEV Manager, are indicated by the yellow color. In such a case, the nodal control price signals, determined by the individual PEV Managers, are overwritten by the S-PEV Manager.

The S-PEV Manager optimization is similarly formulated as the single period PEV Manager optimization:

\[
\max \quad \sum_{n_z = 1}^{N_{\text{zone}}^z} \sum_{v = 1}^{N_V^z(T)} u_{v,n_z}(T, \Omega_{v,n_z}(T), \theta_{v,n_z}(T)) \quad ,
\] 

which can be written out for more clarity to

\[^3\text{Note that voltage violations only occur if a simple load flow algorithm is used as will be shown in Chapter 6. Utilizing an optimal power flow approach as in the preceding chapter avoids such violations without making use of the S-PEV Manager.}\]
Chapter 5. ABM for PEV Demand Management

\[
\max_{n_z=1}^{N_{zone}} \sum_{v=1}^{N_v(T)} \theta_{v,n_z}(T).
\]

\[
\alpha_{v,n_z}(T)C^B_{v,n_z} \left( soc_{v,n_z}(T) - soc^{\min}_{v,n_z} + \frac{p_{v,n_z}^s(T,\theta_{v,n_z}(T)|\Theta_{n_z}(T))}{\varsigma(T)C^B_{v,n_z}} \right)
\]

\[
-\beta_{v,n_z}(T)C^B_{v,n_z} \left( soc_{v,n_z}(T) - soc^{\min}_{v,n_z} + \frac{p_{v,n_z}^s(T,\theta_{v,n_z}(T)|\Theta_{n_z}(T))}{\varsigma(T)C^B_{v,n_z}} \right)^2
\]

\[
-\pi(T)C^B_{v,n_z} \frac{p_{v,n_z}^s(T,\theta_{v,n_z}(T)|\Theta_{n_z}(T))}{\varsigma(T)C^B_{v,n_z}} ,
\]

and which is subject to

\[
p_{v,n_z}^{s,\min}(T) \leq p_{v,n_z}^s(T,\theta_{v,n_z}(T)|\Theta_{n_z}(T)) \leq p_{v,n_z}^{s,\max}(T) , (5.27a)
\]

\[
soc^{\min}_{v,n_z} \leq soc_{v,n_z}(T) \leq soc^{\max}_{v,n_z} , (5.27b)
\]

\[
P_{z}^{\min}(T) \leq \sum_{n_z=1}^{N_{zone}} \sum_{v=1}^{N_v(T)} p_{v,n_z}^s(T,\theta_{v,n_z}(T)|\Theta_{n_z}(T)) \leq P_{z}^{\max}(T) . (5.27c)
\]

The S-PEV Manager incorporates a similar objective, given by (5.25), as the PEV Manager. It is to maximize the utility of all PEVs connected in its zone by ensuring network security on the next higher voltage level. Thus, the S-PEV Manager finds a global optimum for the PEV scheduling problem in its zone z considering operational network limits on his network level and considering the results of its underlying managers.

For simplicity reasons, only the single period S-PEV Manager optimization is formulated in (5.25)–(5.27). The S-PEV Manager optimization takes the setpoints which are determined by the underlying predictive PEV Managers in the particular zone for the current time step as an input. Obviously, the S-PEV Manager controls more PEVs than each underlying manager. The setpoints calculated by the PEV Managers are denoted \( p_{v,n_z}^{s,\max}(T) \). They are utilized as the new upper or lower bound for the power \( p_{v,n_z}^s(T,\theta_{v,n_z}(T)|\Theta_{n_z}(T)) \) which can be assigned to the individual vehicles by the S-PEV Manager, thus
\[
p^{s,\text{max}}_{v,n_z}(T) = p_{v,n_z}\left(T, \theta_{v,n_z}(T) | \Theta_{n_z}(T)\right) \quad \land \quad p^{\text{min}}_{v,n_z}(T) = p^{s,\text{min}}_{v,n_z}(T),
\]
\[
\lor \quad p^{s,\text{min}}_{v,n_z}(T) = p_{v,n_z}\left(T, \theta_{v,n_z}(T) | \Theta_{n_z}(T)\right) \quad \land \quad p^{\text{max}}_{v,n_z}(T) = p^{s,\text{max}}_{v,n_z}(T).
\]

Therefore, the S-PEV Manager either leaves the result found by the PEV Managers unaltered or it reduces the charging setpoint of some cars.

Furthermore, the S-PEV also ensures that each individual car is not overly depleted or overcharged by (5.27b). Finally, the optimization setup considers the maximum (or minimum) power, which can be supplied by the S-PEV Manager, i.e., the 150 kV transformer capacity, in constraint (5.27c). It is denoted \( P^{\text{max}}_z(T) \) and poses the upper bound for the aggregated PEV load in the zone \( z \). This bound can be derived from the transformer rating or from limitations of the lines feeding the transformer.

### 5.6.1 Including Voltage Stability Measures into the S-PEV Manager

Excessive PEV demand can also cause violations of feasible voltage bounds. These lower bounds are typically set at 0.95 p.u. of the operating voltage level. The upper voltage bounds are typically set to 1.05 p.u. Note that the following description for dealing with an excessive voltage drop below the lower voltage bound is also valid for the increase of the zonal voltage beyond the allowed maximum in a V2G case. Changing the tap position of a tap changing transformers can mitigate voltage problems in zones which face excessively low or high voltages. Should the tap variations result in voltages not compliant with the allowed network level boundaries, the S-PEV Manager needs to modify the PEV load in the zone and shift some PEV load to later time intervals. In order to find the maximum load which can be supplied to the PEV fleet in a zone \( z \), the rationale of voltage stability\(^4\) margins can be

\(^4\)Note that voltage stability is inherently a dynamic process and should therefore be tackled by dynamic models. Here, the system disturbance jeopardizing stability is considered to be the increase in load through PEV demand. Thus, voltage stability, in the context used in the following, refers to long term voltage stability. No consideration is paid to short term voltage stability phenomena, and it is assumed that all other dynamics decayed and are in a stable operation point.
used [127–129]. Figure 5.10 shows a situation where the S-PEV Manager needs to reschedule PEVs to keep the voltage in an acceptable range.

Figure 5.10(a) shows a zone which incorporates several PEV Managers on the 11/22 kV level. The managers determine PEV load setpoints which ensure that the maximum load of a transformer station, to which the vehicles are connected, is not violated. This is indicated by the green color of the PEV Manager devices. Here, however, the voltage level in the zone decreases to unacceptable values. This is indicated by the red color of the dots representing the transformer stations and the bus bar to which they are connected. Assuming that the tap changing transformer is not able to resolve the problem, the S-PEV Manger needs to mitigate some of the excessive load in the zone in order to reestablish an acceptable voltage level. For performing the load shift, the S-PEV Manager needs to know the maximum possible PEV load which the zone can supply without violating the minimum voltage bound.

To calculate the maximum possible loading, the dependence of voltage on the load in the zone needs to be determined. The dependence of the complex voltage $U_z$ at the busbar can be modeled using the Thevenin equivalent. This is illustrated in Fig. 5.10(b). The parameters of the Thevenin equivalent, i.e., $E_{th}, R_{th}$ and $X_{th}$, can be found by solving

$$
\begin{bmatrix}
\Re(U_{z,1}) & \Im(U_{z,1}) & -P_{z,1} & -Q_{z,1} \\
-\Im(U_{z,1}) & \Re(U_{z,1}) & Q_{z,1} & -P_{z,1} \\
\Re(U_{z,2}) & \Im(U_{z,2}) & -P_{z,2} & -Q_{z,2} \\
-\Im(U_{z,2}) & \Re(U_{z,2}) & Q_{z,2} & -P_{z,2}
\end{bmatrix}
\begin{bmatrix}
\Re(E_{th}) \\
\Im(E_{th}) \\
R_{th} \\
X_{th}
\end{bmatrix}
= \begin{bmatrix}
\Re(U_{z,1}^2) + \Im(U_{z,1}) & 0 \\
0 & \Re(U_{z,2}^2) + \Im(U_{z,2})
\end{bmatrix},
$$

(5.29)

where $P_{z,1}, Q_{z,1}$ and $P_{z,2}, Q_{z,2}$ denote the active and reactive power consumption of zone $z$ for two load cases while $\Re(\cdot)$ and $\Im(\cdot)$ give the real and imaginary parts of their argument, respectively. Potential load cases incorporate a situation at nominal, i.e. 100%, PEV load and where PEV load is reduced to 90 % of the nominal PEV load in the particular zone.
5.6. Developing a Supervisory PEV Manager

Thevenin equivalent of the zone

Figure 5.10: (a) Zone fed by a 150 kV tap changing transformer. An S-PEV Manager controls the underlying PEV Managers which subsequently control the PEVs connected to the each 11/22 kV transformer station. Overly low voltages are indicated by the red color.

(b) Thevenin equivalent of the zone depicted in Fig. 5.10(a) and its load. The Thevenin equivalent is used to determine the maximally allowed load for all underlying PEV Managers. This ensures compliance with voltage stability limits.
Having found the parameters of the Thevenin equivalent, the relation

$$U_z^4 + (2P_z R_{th} + 2Q_z X_{th} - E_{th}^2)U_z^2 + (P_z^2 + Q_z^2)(R_{th}^2 + X_{th}^2) = 0 \quad (5.30)$$

can be derived from the Thevenin-circuit. The derivation is given in the Appendix through (E.1)–(E.22). Setting $U_z$ to the minimum acceptable voltage for the zone and adding a margin for the lowest nodal voltage within the zone, a maximum active power consumption $P_{z,\text{Voltage,max}}$ can be derived. This amount can be supplied to the PEV fleet without causing violations of voltage limits. The maximum active power amount which is derived from the voltage relation can subsequently be used as the upper bound in constraint (5.27c) of the S-PEV Manager.

Figure 5.11 visualizes the principle of the S-PEV Manager ensuring a proper voltage level in zone $z$. The figure shows the load-voltage dependence in a zone. The red dot indicates the voltage of the zone at the current PEV load situation without management through the S-PEV Manager. The load in the zone, which comprises an uncontrollable part and the flexible PEV load, is too high and therefore the voltage of the zone, $U_{\text{act}}$, is lower than the allowed minimum. Using the Thevenin equivalent, a maximum load for the complete zone can be calculated. This load is indicated by $P_{\text{max,Thevenin}}$ and the dotted, green, vertical line. Using this result, the maximum possible PEV load which does not violate the voltage bounds can be determined. The S-PEV Manager then uses this value to shift excessive PEV load to later times, thus reducing the total consumed power in the zone. This avoids undervoltages and translates the network state into the one indicated by the black dot. Undervoltages are avoided. Chapter 6 provides case studies featuring the S-PEV Manager and exemplifies its functionality.

5.7 Tuning the Utility Function Parameters to achieve Valley Filling and Peak Shaving

According to Section 5.2.2, the parameters $\alpha_{v,n}, \beta_{v,n}$ are so far considered to be constant over time. Tuning the parameters in relation to a price level, which is exogenously given, e.g., based on a real time price signal, allows to control the charging behavior of a PEV fleet. The goal is generally to control the charging behavior such that the PEVs will
5.7. Valley Filling and Peak Shaving with PEVs

Figure 5.11: S-PEV operation principle for ensuring voltage stability measures.

mostly charge during low system load periods thereby avoiding an increase of the overall system load peak. This is commonly referred to as valley filling [8, 90]. As a second step, utilizing V2G services of aggregated PEV fleet, the system’s peak load could be reduced which is commonly referred to as peak shaving [130–132]. However, before actually tuning the utility function parameters, the concept of reachable levels is introduced.

5.7.1 Introducing the concept of reachable levels for valley filling and peak shaving

In order to perform valley filling and peak shaving, the aggregator needs to assess the amount of energy which can actually be shifted into low load periods. This amount is strongly dependent on the charging flexibility of the vehicles, i.e., on the ratio between the vehicle’s minimum charging time and its parking duration. In case the ratio is one, the aggregator is not able to shift the load of the vehicle temporally. Then, the vehicle needs to charge continuously when parked. The lower the ratio is, the higher is the charging flexibility of the particular vehicle. Based on this flexibility a so called reachable load level can be calculated which determines the maximum load level during a predefined time period. This load level models a situation where the load of the PEV fleet is distributed over this time period.
A reachable level can be calculated during low as well as during high load periods. While uncontrolled charging can aggravate existent load peaks, the calculation of a reachable level for high load periods allows to distribute the PEV load temporally, thereby avoiding load peaks. To determine the reachable level during a time period, the total energy which needs to be charged by the connected PEVs during this particular time period needs to be calculated.

Figure 5.12 shows how the flexibility and the load, during, e.g., the high load period (HLP) of a system, can be calculated. First, the duration of the period needs to be determined. This can be performed by the aggregator based on the underlying, known load evolution in the system. The load curve can either represent a city, where the aggregator is operating, or the whole country. The definition of the time periods is visualized by the vertical, blue, dotted lines. As a second step, the amount of energy which has to be charged by one vehicle during its parking duration is calculated by
5.7. Valley Filling and Peak Shaving with PEVs

\[ \Delta E_{v,n} = (soc_{\text{desired}}^{v,n} - soc_{\text{arrival}}^{v,n}) C^{B}_{v,n} \eta_c. \]  

(5.31)

All or a part of this energy has to be charged during a specific load period, either LLP or HLP. Four different cases of how vehicles can behave during a load period, e.g., during the HLP, are illustrated in the lower part of Fig. 5.12. Vehicle 1 is parked only during the HLP. Its parking duration is indicated through the black horizontal line. The time needed in order to charge the desired amount of energy is shown by the colored bar below the black line. The level of charging flexibility is indicated by the color of the bar, i.e., a red color indicates a low charging flexibility and a green color means a high charging flexibility.

For vehicle 1, its complete desired energy needs to be charged during the HLP. Furthermore, as the time to charge this energy is almost as long as the parking duration, the bar is colored red. This vehicle incorporates little flexibility when being charged. For the other vehicles the situation is different. Vehicle 2 and vehicle 3 are both parked during the LLP and the HLP. Both vehicles offer more charging flexibility than vehicle 1, and vehicle 2 offers more charging flexibility than vehicle 3. Both vehicles offer the potential to be charged mainly during the LLP. Vehicle 4 offers the highest charging flexibility. The fraction of energy which is charged during the HLP is calculated by

\[ \Delta E_{v,n}^{\text{HLP}} = \Delta E_{v,n} \frac{PD_{v,n}^{\text{HLP}}}{PD_{v,n}}, \]

(5.32)

where \( PD_{v,n}^{\text{HLP}} \) denotes the vehicle’s parking duration during the HLP and \( PD_{v,n} \) indicates its total parking duration. Note that this approach assigns more load to the HLP than assuming that vehicles would be charged with maximum power during the LLP thereby avoiding load during HLP. This approach is not pursued here as it would remove a lot of charging flexibility during the LLP. However, it proves to be favorable to allow some charging flexibility during the LLP. Other vehicles, which incorporate no charging flexibility from the start, could then cause the aggregated load of the PEV fleet to exceed the reachable level if the available flexibility is limited.

The energy which is needed to determine the reachable level during the particular period is given by

\[ E_{\text{reach,HLP}} = \sum_{n=1}^{N} \sum_{v=1}^{N_v} \Delta E_{v,n}^{\text{HLP}}. \]

(5.33)
Based on this value a reachable load level $L^{\text{reach},\text{HLP}}$ can be calculated according to

$$E^{\text{reach},\text{HLP}} = \frac{\tau(T)}{3600[\text{s}]} \sum_{T=T_{\text{start}}^{\text{HLP}}}^{T_{\text{end}}^{\text{HLP}}} H(L^{\text{reach},\text{HLP}} - L(T))(L^{\text{reach},\text{HLP}} - L(T)),$$

(5.34)

where the variable $\tau(T)$ gives, again, the length of time step $T$ in seconds, $L(T)$ denotes the load in time step $T$ and $H$ denotes the Heaviside function. The reachable load level is calculated the same way for the LLP.

A conceptual illustration of the reachable level approach is shown in Fig.5.13, where the blue area shows $E^{\text{reach},\text{LLP}}$, which is the energy to be charged during LLP. The second reachable level, colored in orange, illustrates energy which is charged during the HLP. The system load exceeding the second reachable level, i.e. the reachable level during the HLP, is indicated in red. The vehicles can be used to supply this load thereby performing peak shaving in the system.
5.7. Valley Filling and Peak Shaving with PEVs

5.7.2 Tuning of Utility Function Parameters in order to achieve Valley Filling and Peak Shaving

Having determined the reachable levels, the aggregator can tune the utility function parameters of its fleet in order to impose the desired charging behavior. Before tuning the parameters, the benefit and the utility function have to be analyzed in order to investigate how the parameters influence the charging behavior of the cars and to avoid inconsequential charging/discharging behavior. The utility function is extended in order to incorporate V2G behavior. This extension allows then to include peak shaving in the model. Finally, an algorithm is presented to tune the utility function parameters.

Analysis of the benefit and the utility function for charging purposes (Grid to Vehicle (G2V))

The benefit function attributes a value to the energy stored in the battery of a particular vehicle. This value needs to be positive in order to be meaningful and to achieve a charging behavior of the connected fleet. Investigating the boundary case of the benefit function gives

\[
\frac{b_{v,n}(\Omega_{v,n}(T))}{\alpha_{v,n}\Omega_{v,n}(T) - \beta_{v,n}\Omega_{v,n}(T)^2} = 0 \Rightarrow \Omega_{v,n}(T) = 0 \lor \Omega_{v,n}(T) = \frac{\alpha_{v,n}}{\beta_{v,n}}.
\]

from which follows that

\[
\Rightarrow \Omega_{v,n}(T) = 0 \lor \Omega_{v,n}(T) = \frac{\alpha_{v,n}}{\beta_{v,n}}.
\]

Hence, the zeros of \(b_{v,n}\) are found for

\[
\begin{align*}
\text{For } \alpha_{v,n} \geq \beta_{v,n} \text{ it follows that } soc_{v,n}(T) + q_{v,n} &= soc_{v,n}^{\text{min}} \\
\lor soc_{v,n}(T) + q_{v,n} &= \frac{\alpha_{v,n}}{\beta_{v,n}} + soc_{v,n}^{\text{min}}.
\end{align*}
\]

For \(\alpha_{v,n} \geq \beta_{v,n}\) it follows that \(soc_{v,n}(T) + q_{v,n} \geq 1\). Be reminded that the benefit function has the shape of a parabola. Setting the maximum of the benefit function outside of the feasible operating bounds of the battery ensures that the desire to charge increases until the feasible energy bound is reached. This is a necessary condition to ensure consistent charging behavior. The condition has to be considered when tuning the
utility function parameters. In order to derive conditions for the parameters, the first derivative of the benefit function is set to zero:

$$\frac{db_{v,n}}{dq_{v,n}} = 0 ,$$

(5.38)

and one can then calculate

$$\theta_{v,n}(T)C^B_{v,n}\alpha_{v,n} - 2\theta_{v,n}(T)C^B_{v,n}\beta_{v,n}\Omega_{v,n}(T) = 0 ,$$

(5.39)

which gives

$$\Leftrightarrow (soc_{v,n}(T) - soc^{\text{min}}_{v,n} + q_{v,n}) = \frac{\alpha_{v,n}}{2\beta_{v,n}} .$$

(5.40)

Setting $\beta_{v,n} \geq 0$ and the SOC to its maximum gives that $\alpha_{v,n} \geq 2\beta_{v,n}(1 - soc^{\text{min}}_{v,n})$. Therefore, the maximum of the benefit function lies beyond the bound $soc_{v,n}(T) = 1 - soc^{\text{min}}_{v,n}$. This causes the marginal benefit to be positive for the range of feasible SOC states.

In order to find a proper value for $\beta_{v,n}$, the case of $\pi(T) = \pi^{\text{min}}_{\text{day}}$ is investigated. This situation, together with the highest value of $\theta_{v,n}(T) = \theta^{\text{max}}_{v,n}$, offers the highest incentive to the vehicles to charge. For the computation of the lower bound of $\beta_{v,n}$, the first derivative of the utility function for the charging mode:

$$\frac{du^{\text{G2V}}_{v,n}}{dq_{v,n}} = 0 ,$$

(5.41)

gives

$$\theta^{\text{max}}_{v,n}C^B_{v,n}\alpha_{v,n} - 2\theta^{\text{max}}_{v,n}C^B_{v,n}\beta_{v,n}\left(\Omega_{v,n}(T)\right) - C^B_{v,n}\pi^{\text{min}}_{\text{day}} = 0 .$$

(5.42)

This is equivalent to

$$\Leftrightarrow \beta_{v,n} = \frac{\alpha_{v,n} - \pi^{\text{min}}_{\text{day}}/\theta^{\text{max}}_{v,n}}{2 \cdot (soc_{v,n}(T) + q_{v,n} - soc^{\text{min}}_{v,n})} ,$$

(5.43)

assuming that the vehicle is fully recharged gives

$$\beta_{v,n} = \frac{\alpha_{v,n} - \pi^{\text{min}}_{\text{day}}/\theta^{\text{max}}_{v,n}}{2(1 - soc^{\text{min}}_{v,n})} ,$$

(5.44)

\footnote{Remember that the maximum value of the personal energy valuation parameter is dependent on (5.2) and is limited to 5.}
which gives that the vehicle with the highest energy valuation and a fully charged battery will incorporate a marginal utility of zero. Note that this definition of $\beta_{v,n}$ fulfills the conditions derived from (5.38)–(5.40).

Setting the derivative of the utility function to zero and rearranging for $q_{v,n}$ allows one to determine the amount of energy which is charged by a vehicle of the fleet given the tuned parameters $\alpha_{v,n}, \beta_{v,n}$. Performing the derivation for the general case of $\theta_{v,n}(T)$ gives

$$q^{G2V}_{v,n} = \frac{\alpha_{v,n} - 2 \cdot \beta_{v,n} \cdot (soc_{v,n}(T) - soc_{v,n}^{\min}) - \pi(T)/\theta_{v,n}(T)}{2 \cdot \beta_{v,n}}, \quad (5.45)$$

where (5.44) can be inserted which results in

$$q^{G2V}_{v,n} = \frac{\alpha_{v,n} - \left(\frac{\alpha_{v,n} - \pi_{\text{max}}/\theta_{v,n}^{\max}}{(1 - soc_{v,n}^{\min})}\right) \cdot (soc_{v,n}(T) - soc_{v,n}^{\min}) - \pi(T)\theta_{v,n}(T)}{\alpha_{v,n} - \pi_{\text{max}}/\theta_{v,n}^{\max}}. \quad (5.46)$$

Obviously, the amount of energy is then only dependent on $\alpha_{v,n}$. Note that one has $q_{v,n} = q^{G2V}_{v,n}$ which indicates that the energy amount $q_{v,n}$ is derived from the utility function of a charging situation, hence $q^{G2V}_{v,n} \geq 0$. Computing the derivative of $q^{G2V}_{v,n}$ with respects to the utility function parameter $\alpha_{v,n}$ gives

$$\frac{dq^{G2V}_{v,n}}{d\alpha_{v,n}} = \frac{\pi(T)\theta_{v,n}(T) - \pi_{\text{min}}/\theta_{v,n}^{\max}}{(\alpha_{v,n} - \pi_{\text{max}}/\theta_{v,n}^{\max})^2}. \quad (5.47)$$

This term is always positive since $\pi(T)/\theta_{v,n}(T)$ is always bigger than $\pi_{\text{min}}/\theta_{v,n}^{\max}$ and therefore a higher energy consumption can be expected when increasing $\alpha_{v,n}$.

With an increasing $\alpha_{v,n}$, avoiding negative values of $\alpha_{v,n}$ and $\beta_{v,n}$, and having a price signal $\pi(T)$ which gives that $\pi(T)/\theta_{v,n}(T) \geq \pi_{\text{min}}/\theta_{v,n}^{\max}$ results in a positive $q^{G2V}_{v,n}$. This expresses that charging can be expected by this particular vehicle.

Figure 5.14 illustrates how tuning of $\alpha_{v,n}$ influences the charging behavior of a vehicle assuming $\theta_{v,n}(T) = 1$. The figure shows three possible outcomes of the tuning process performed in time step $T$. The particular situation is indicated by the superscripts. In the first case, the value of $\alpha_{v,n}^{\text{Case1}}(T)$ is relatively high. The vehicle is charged to the SOC at which
the marginal benefit weighted by the personal energy valuation intersects the current price signal $\pi(T)$. This SOC is denoted $soc_{\text{Case}1}^{\text{V}}(T)$. In the second case, the value of $\alpha_{\text{Case}2}^{\text{V}}(T)$ is smaller and hence the vehicle is charged only to $soc_{\text{Case}2}^{\text{V}}(T)$. The third case shows a situation where the value of $\alpha_{\text{Case}3}^{\text{V}}(T)$ is smaller than the current price and is also smaller than the minimum price signal during the day. This vehicle is not charged in this situation. Note that the marginal benefit is fixed in its value at $soc_{\text{max}}^{\text{V}} = 1$ which is in accordance with (5.44). In the figure, the charging power is assumed not to be limited.

Achieving peak shaving behavior by adapting the utility function (Vehicle to Grid (V2G))

The utility function needs to be adapted for the V2G case as battery costs and the cost of the energy, which is discharged during peak load times, have to be considered. The utility function, which is so far used for charging situations, is adapted to

$$u_{\text{V2G}}^{\text{V}}\left(\Omega_{\text{V},n}(T), \pi(T), \theta_{\text{V},n}(T)\right) =$$

$$\theta_{\text{V},n}(T)\alpha_{\text{V},n}C_{\text{V},n}^{\text{B}}\left(\Omega_{\text{V},n}(T)\right) - \theta_{\text{V},n}(T)\beta_{\text{V},n}C_{\text{V},n}^{\text{B}}\left(\Omega_{\text{V},n}(T)\right)^2 - \left(\pi_{n}(T) - \frac{\pi_{\text{min}}^{\text{day}}}{\eta_{\text{s}}\eta_{\text{c}}} - \frac{\pi_{\text{batt}}}{\eta_{\text{s}}}\right)C_{\text{V},n}^{\text{B}}q_{\text{V},n}(T, \theta_{\text{V},n}(T)|\Theta_{n}(T)).$$

(5.48)
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It is assumed that the energy which is discharged during peak load hours can be reacquired for at a lower energy price. Battery costs are included on the basis of the model found in [133]. The parameter $\beta_{v,n}(T)$ is determined by (5.44). Then, with the adapted utility function, the individual discharging behavior can be determined according to

$$q_{v,n}^{V2G} = \frac{\alpha_{v,n} - \pi(T) - \frac{\pi_{\text{max}}^{\text{day}}}{\pi_{\text{max}}^{\text{day}}}}{\theta_{v,n}(T) - \frac{\pi_{\text{min}}^{\text{day}}}{\pi_{\text{max}}^{\text{day}}}} - (soc_{v,n} - soc_{v,n}^{\text{min}}). \quad (5.49)$$

The superscript $V2G$ indicates that the calculated energy amount is strictly valid for a discharging situation, hence $q_{v,n}^{V2G} \leq 0$. In order to integrate the peak shaving option into the PEV Manager utility function, which so far only modeled charging behavior, one can utilize a mixed integer nonlinear formulation. However, this proves computationally expensive, especially since large numbers of vehicles must be considered. This can be bypassed by closely investigating both parts of the integrated utility function and eliminating degrees of freedom.

Figure 5.15 illustrates both parts of the integrated utility function for four different cases when tuning $\alpha_{v,n}$. In Fig. 5.15(a) the two different utility function parts reach their maximum for positive values of $q_{v,n}^{G2V}$ and $q_{v,n}^{V2G}$. However, $u_{v,n}^{V2G}$ is not defined for positive values and hence only $u_{v,n}^{G2V}$ can be used. This is a valley filling situation. In Fig. 5.15(b) both utility function parts reach a maximum in the left half plane but...
only $u_{v,n}^{V2G}$ is defined here. This is a typical peak shaving situation. Figure 5.15(c) shows maxima for both utility function parts lying in areas where both functions are defined. In this case, both utility functions would need to be calculated. However, since one can assume that the controlling entity would like to impose a consistent charging behavior on the PEV fleet, only one utility function part should be chosen. Figure 5.15(d) shows a maximum of $u_{v,n}^{G2V}$ lying in the negative half plane and a maximum of $u_{v,n}^{V2G}$ lying in the positive. Both utility functions are not defined for these values of $q_{v,n}$. Hence, the best solution can be achieved for $q_{v,n} = 0$.

**Tuning of the utility function parameters**

The parameters need to be tuned in such a way that the aggregated charging or discharging behavior complies with the reachable level determined before. Using the difference between the reachable level and the underlying system load, an average amount of energy, which needs be charged by the connected PEVs can be calculated. This average energy amount allows for reaching the predefined reachable load level in the time step $T$. This desired average amount of energy, $q_{v,n}^{G2V,avg,des}(T)$, to be charged is determined by

$$q_{v,n}^{G2V,avg,des}(T) = \frac{H \left(L_{reach,1} - L(T)\right) \left(L_{reach,1} - L(T)\right)}{4C_{V,n}^{B}N_{V}(T)} ,$$

(5.50)

using the already introduced notation. Note that $\sum_{n=1}^{N} N_{n}^{V}(T) = N^{V}(T)$.

In the case where peak shaving has to be performed, the desired average energy to be discharged during the intervals can be calculated according to

$$q_{v,n}^{V2G,avg,des}(T) = \frac{H \left(L_{reach,2} - L(T)\right) - 1 \left(L_{reach,2} - L(T)\right)}{4C_{V,n}^{B}N_{V}(T)} .$$

(5.51)

Now, with the foregoing explanations in mind, one can determine an appropriate $\alpha'_{v,n}$ in order to obtain the desired value of $q_{v,n}^{G2V/V2G,avg}(T)$ of the connected fleet. In the following, the $\alpha'_{v,n}$ is referred to as $\alpha_{v,n}^{tuned}$. 
The computation of $\alpha_{v,n}^{\text{tuned}}$ is performed before each time step. Therefore, the parameters become dependent on $T$, hence

$$
\begin{align*}
\alpha_{v,n} & \rightarrow \alpha_{v,n}^{\text{tuned}}(T), \\
\beta_{v,n} & \rightarrow \beta_{v,n}^{\text{tuned}}(T).
\end{align*}
$$

Reasonable starting bounds for the determination of $\alpha_{v,n}^{\text{tuned}}(T)$ are chosen to be

$$
\alpha_{v,n}^{\text{min}} = \pi_{\text{day}}^{\text{min}} + \epsilon; \quad \epsilon < < 1,
$$

as the lower starting bound in order to prevent division by zero and

$$
\alpha_{v,n}^{\text{max}} = 5\pi_{\text{day}}^{\text{max}},
$$

as the upper starting bound in order to allow a large tuning flexibility during phases when the price signal is high. Using lower values for the upper bound would lead to less charging during the high price signal periods, possibly leading to a deviation from the reachable load level.

The following procedure allows a fast determination of a suitable value for $\alpha_{v,n}^{\text{tuned}}(T)$:

1. The lower bound $\alpha_{v,n}^{\text{min}}$ and the higher bound $\alpha_{v,n}^{\text{max}}$ are set.

2. Then the average of $\alpha_{v,n}^{\text{min}}$ and $\alpha_{v,n}^{\text{max}}$ is computed and chosen to be the actual $\alpha_{v,n}^{\text{tuned},i}$, where $i$ refers to the iteration: $\alpha_{v,n}^{\text{tuned},i}(T) = \frac{\alpha_{v,n}^{\text{min}} + \alpha_{v,n}^{\text{max}}}{2}$. The iteration stops if the difference between the new $\alpha_{v,n}^{\text{tuned},i}(T)$ and the one from the iteration before, $\alpha_{v,n}^{\text{tuned},i-1}(T)$, is smaller than a certain value $\delta_\alpha$ chosen to 0.005. It defines the convergence criterion for this algorithm. The last value for $\alpha_{v,n}^{\text{tuned},\text{end}}(T)$ is retained.

3. The variable $q_{G2V/V2G}^{\text{G2V}/\text{V2G},i}(T, \alpha)$ is then calculated for $\alpha_{v,n}^{\text{tuned},i}(T)$, $\alpha_{v,n}^{\text{min}}$ and $\alpha_{v,n}^{\text{max}}$. Note the additional dependability on $\alpha$ as it is now becomes a variable. Since the SOC of the different PEVs is known, $q_{G2V/V2G}^{\text{G2V}/\text{V2G},i}(T, \alpha_{v,n}^{\text{tuned},i})$ can easily be calculated using (5.46) taking into account the current price signal. Then, $q_{G2V/V2G,\text{avg},i}^{\text{G2V}/\text{V2G},i}(T, \alpha_{v,n}^{\text{tuned},i})$ is computed by summing the values $q_{G2V/V2G}^{\text{G2V}/\text{V2G},i}(T, \alpha_{v,n}^{\text{tuned},i})$ and dividing by the number of the vehicles. This calculation is computationally inexpensive.
4. Two cases are differentiated:

- \[ |q_{G2V/V2G,avg}^{G2V/V2G,avg}(T, \alpha_{\text{min}}^v,n)| \leq |q_{G2V/V2G,avg,\text{des}}(T)| \\wedge \]
  \[ |q_{G2V/V2G,avg}(T, \alpha_{\text{tuned},i}^v,n(T))| \geq |q_{G2V/V2G,avg,\text{des}}(T)| \]

In this case, \( \alpha_{\text{min}}^v,n \) is chosen to be the new lower bound and \( \alpha_{\text{tuned},i}^v,n(T) \) is chosen as the new upper bound.

- \[ |q_{G2V/V2G,avg}(T, \alpha_{\text{tuned},i}^v,n(T))| \leq |q_{G2V/V2G,avg,\text{des}}(T)| \\wedge \]
  \[ |q_{G2V/V2G,avg}(T, \alpha_{\text{max}}^v,n)| \geq |q_{G2V/V2G,avg,\text{des}}(T)| \]

In this case, \( \alpha_{\text{tuned},i}^v,n(T) \) is chosen to be the new lower bound and \( \alpha_{\text{max}}^v,n \) is chosen as the new upper bound.

5. The iteration is restarted from the first step again.

At the end of the iteration, the a value for \( \alpha_{\text{tuned}}^v,n(T) \), meaning the one that gives rise to \( q_{G2V/V2G,avg}(T, \alpha_{\text{tuned}}^v,n(T)) \) close to the desired average energy to be consumed, is retained. Then \( \beta_{\text{tuned}}^v,n(T) \) is determined using equation (5.44). Having determined \( \alpha_{\text{tuned}}^v,n(T) \) and the slope of the marginal utility function, the charging behavior of each individual vehicle is controlled appropriately.

Simulation examples

In the following, three simulation examples are presented which use the tuning method described above. The needed knowledge on the PEV behavior is again provided by an agent based transportation simulation, as in the example in Chapter 5.5. The transportation simulation is described in detail in Chapter 6. The daily agent behavior includes activities such as staying at home, going to work, education, shopping and leisure activities, all located in a big, Swiss city. The transportation simulation output provides information on when the vehicles are parked and on the amount of energy with which each vehicle has to be charged during its parking time. This information is necessary in order to determine the reachable load levels as illustrated in to Fig. 5.12. In this example, between 170'000 and 230'000 vehicles are connected for charging.

The framework developed in Chapter 3 is applied in all examples. Vehicles, which have to charge in order to attain their desired SOC, leave
the controlled charging mode and charge in the uncontrolled mode at full connection power. The cars in uncontrolled mode are considered in the overall load level and influence the tuning of the utility function parameters. Furthermore, for simplicity, a constant price signal is assumed in the first two examples where only charging is simulated. In the third example an artificial high price period is used during peak load hours in order to foster V2G behavior. No real network has been taken into consideration, i.e., no constraints are imposed by network assets. Here, the network acts as a copperplate.

The result of the first example is illustrated in Fig. 5.16. The tuning of the parameters avoids load peaks from PEV charging in the city. The black, dotted line plots the city’s base load. Obviously, it incorporates a high load and a low load period, similar to Fig. 5.12. The red, dashed line shows the load of the city if all vehicles are charged in uncontrolled mode. It can be seen that the additional load introduced by the vehicles is substantial. Uncontrolled charging leads to a high load peak at 09:30. During night hours, the load drops to a level close to the base loading of the system, e.g., at 04:00.

The load curve of the PEV fleet is substantially modified by the controlled charging approach. It is illustrated through the green curve and follows a rectangular shape according to the reachable levels calculated with (5.34). Load peaks during the day are avoided. Instead, a load plateau is created. The maximum load is reduced from 915 MW to 772 MW. During the night hours the load valley is filled. The load level stays rather constant at 485 MW. The approach takes full advantage of the vehicles’ charging flexibility. The load level in the controlled charging case exceeds the reachable level between 20:00 and 23:00 due to vehicles which charge in uncontrolled mode. During this period, their load cannot be compensated by switching other vehicles off.

Figure 5.17 illustrates the impacts of the vehicle fleet’s charging behavior on the load curve of a country. Here, Switzerland is chosen as the country of reference. Again, the black, dotted graph shows the countries load curve without electric vehicles. The red, dashed and the green line show the load for the uncontrolled and the controlled, i.e., tuned, case, respectively. It can be seen that the country’s peak load is increased. In the controlled case, the country’s peak load is increased less than in the uncontrolled charging case. The load level during the low load hours between 24:00 and 06:00 is increased substantially compared to the uncontrolled charging case.
Figure 5.16: Simulation of valley filling behavior of a large PEV fleet in a city.

Figure 5.17: Simulation of valley filling behavior for a large PEV fleet in a city and its effect on the country load curve.
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Figure 5.18: Simulation of valley filling behavior for a PEV large fleet in a country.

Figure 5.19: Simulation of valley filling behavior for a large PEV fleet in a country and its effect on the city load curve.
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The second example performs valley filling for the country load curve, i.e., it takes the country load curve as input. The utility function parameters are tuned in order to fill the valley of the country’s load curve. The result is illustrated in Fig. 5.18. The valley hours between 24:00 and 05:00 now exhibit a load plateau higher than in the previous example. Later, the load curve is quite similar to the one before. However, the load until 11:00 is lower in the controlled case than in the example before. Here, only PEVs charge which are in the uncontrolled mode. they have to charge in order to attain their desired battery energy level before departure. Load is shifted to the late afternoon or, if possible, into the night.

Figure 5.19 shows the impact of the valley filling behavior for the country on the underlying load curve of the city. The shape which is dominated by two plateaus in the last example is altered. Now, it incorporates many load peaks and the maximum load is barely reduced. The load peak in the city occurs later than in the uncontrolled case as much charging is shifted away from the country’s load peak time at 11:30. The load valley hours at night are filled. The load during the night shape exhibits a rather spiky behavior. This behavior is determined by the country’s load curve.

The third example shows how the electric vehicle fleet can be utilized to perform peak shaving and valley filling taking the country’s load curve as the reference. As seen in Fig. 5.20, the country’s load valley during the night hours is filled with PEV load and a load plateau is created. A little load plateau starting at 07:15 can be seen due to the second reachable level. The load which is imposed by vehicles between 07:30 and 09:00 is solely due to vehicles in the uncontrolled charging mode. In order to reduce the load during phases when the load is particularly high, a third reachable level is introduced. Without the additional level, vehicles would start to discharge at 08:00 in this example. As there is only a small number of vehicles and, additionally, the vehicles, which arrive after 08:00 feature an almost empty battery, peak shaving behavior would end before the overall load system peak is reached. Even worse, vehicles, whose batteries are completely discharged, would transfer into the uncontrolled charging mode and increase the overall system load peak beyond the one of the uncontrolled case.
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Figure 5.20: Simulation of valley filling and peak shaving behavior for a large PEV fleet in a country.

Figure 5.21: Simulation of valley filling and peak shaving behavior for a large PEV fleet in a country and its effect on the city load curve.
Using the third reachable level, the load peaks between 09:00 and 12:00 are reduced. During this period, only a small part of the base load is supplied by the PEV fleet. This is due to electric vehicles charging in uncontrolled mode and imposing a substantial additional load. This additional load is supplied by the PEVs in V2G mode. The energy which is discharged between 09:00 and 12:00 has to be reacquired as each individual car has to attain the desired SOC. Therefore, the load in the controlled case is higher between 14:00 and 18:00 than in the uncontrolled case. Note that the load level between 12:00 and 18:00 is marginally higher than in the second example where peak shaving is not performed. This is due to vehicles which drop out of the controlled mode as they have to be charged immediately to attain their desired SOC at departure.

After 18:00 as much load is shifted to the low load period as possible. However, only a small difference between the load curves, representing uncontrolled and controlled charging behavior, is seen. Often, cars which charge late in the day have more trips planned. These vehicles often do not offer enough charging flexibility to postpone their charging until the load valley hours.

The impact of the peak shaving and valley filling charging behavior on the city’s load curve is illustrated in Fig. 5.21. It can be seen that the load is increased during the low load period of the city. The load curve in the controlled charging case incorporates many load peaks. During the V2G mode, only little power is fed back to the transmission system. In fact, this occurs only at 11:15. Otherwise, vehicles which feed power back to the system compensate the power drawn by other vehicles, charging in uncontrolled mode.

5.8 Concluding Remarks

This chapter develops a PEV demand management scheme which relies on game theoretic concepts and agent based modeling. The scheme is extended to a distributed, predictive and a hierarchical structure which can be integrated into power systems as they also are hierarchical. The scheme considers transformer capacity limits and feasible voltage bounds. Line flow limits have been neglected for load flows but could be incorporated, e.g., through an optimal power flow scheme.
Management algorithms which are not based on agent theory, could also have been utilized to schedule the charging or discharging of PEVs in the network. However, as each PEV is individually simulated by the transportation model, this calls for a demand management approach which utilizes a similar theoretical background, thus allowing for an unequivocal and integrated electric mobility framework. In summary, the individual treatment of the PEVs by the agent based demand management approach, although being computationally slow, proves to incorporate substantial operational flexibility.

Tuning the agents utility function parameters, e.g., based on adequate aggregator contracting, allows for valley filling and peak shaving. This approach illustrates good controllability even though each vehicle is treated individually. Usually similar results are attained when heavily simplifying the problem and assuming one aggregated storage. Obviously, the latter is much easier to control. It should be noted that the definition of the goal for the charging behavior is important when tuning the utility function. Achieving valley filling behavior on a country wide scale can cause load peaks in cities. These peaks could potentially stress the infrastructure in the city. On the other hand, achieving valley filling in cities only could be asset friendly but does not necessarily lead to valley filling on a country wide scale.
Chapter 6

An Integrated Model of Vehicle, Transportation and Power Systems

This chapter develops an integrated model for the analysis of electric mobility. Models, which are described in Chapter 4 and in Chapter 5, are integrated with an agent based transportation simulation and a vehicle fleet simulation. This fusion allows to investigate the spatial and temporal driving and charging behavior of large numbers of PEVs in detail. First, the evolution of the vehicle fleet in the coming decades is simulated in order to determine the share and the type of PEVs. Then, the simulated portfolio of cars along with the particular energy consumption models are used in the transportation simulation to determine the charging time, location and the SOC of the PEVs. This information is then used for the PEV Managers, which charge the vehicles intelligently.

A smart charging scheduling algorithm is developed. It takes into account that, due to infrastructure limitations, not all vehicles can be charged accordingly throughout the day at the different locations. As this could change the simulated mobility patterns, the information on network congestion is fed, together with the mobility demand, to a centralized charging scheduler. The scheduler then determines how and where each individual vehicle is charged. Finally, a large case study of the distribution network of Zurich, Switzerland is performed.
Chapter 6. An Integrated Model for PEV Analysis

6.1 Motivation for an Integrated Modeling Approach

The large scale utilization of PEV technology will introduce additional load to the power system. The temporal and spatial behavior of PEVs is hard to predict as PEVs are inherently mobile. Furthermore, the amount of new load as well as the overall energy demand is also hard to anticipate. This does not seem impedient, but becomes crucial as the power system can be regarded as virtually static compared with the transportation system. A large number of PEVs connecting in one area might cause asset stress as well as voltage stability problems [73]. The foregoing chapter develops management schemes to avoid such challenging impacts.

In order to gather knowledge on electric vehicle behavior, fleet tests can be performed [134] but for efficient forecast and analysis tools, new models need to be developed. Transportation simulation models could be used for the investigation of spatial and temporal vehicle connection patterns [75]. These models, however, are limited by their lack of ability to incorporate specific energy demands of the simulated vehicles. A model, which can offer accurate insights into temporal and spatial load evolution, energy demand and possible environmental footprints of electrified individual transportation, needs to consider power and transportation systems as well as the technologies employed by the simulated vehicles. Figure 6.1 illustrates the domains which are integrated in the following.

The results from such a detailed model are mutually useful to all three domains [61]. Focussing on power systems, the results could be utilized for the analysis of load management potential, e.g., valley filling [135],
of PEV scheduling potential, of the balancing potential for fluctuating power infeed from renewable energy sources [100] or for the analysis of the potential for providing ancillary services [37, 38, 102, 136].

In the following, a possible architecture of such an integrated analysis tool is illustrated and its functionality as well as the individual parts are elaborated. The focus is laid upon the transportation simulation as the PEV demand management is described in the previous chapter. It is described how the transportation simulation and the demand management scheme, both relying on agent based modeling (ABM), are integrated. Finally, the model is applied to a real power system of a metropolitan area. Case studies show results for different PEV scenarios.

6.2 Architecture and Functionality of the Integrated Model

6.2.1 General architecture

Figure 6.2 illustrates the architecture of the method developed herein. It consists of the combination of three independent models, the Vehicle Technology Assessment Model (VTAM), the Multi Agent Transportation Simulation (MATSim) and the PEV Management and Power System Simulation (PMPSS). The models are linked and rely on outputs of each other.

The PMPSS integrates PEVs into the power system and offers a charging management scheme for the vehicles, which is based on Chapter 5. A possibility to analyze the availability of their aggregated storage within PMPSS and use it for V2G purposes is described later in Chapter 7.

The VTAM comprises two features. Firstly, the evolution of the future vehicle fleet can be simulated to determine the fractions of the different powertrain technologies within the fleet. Secondly, it constitutes models of the respective powertrains, which, when fed with real world drive cycles, provide the individual energy demands of the vehicles while have being driven. In the case of electric vehicles the primary energy and CO₂ emissions (as a function of the electricity supply system under considerations) can be calculated. For conventional vehicles the petrol consumption can be determined.
MATSim simulates transportation behavior using large amounts of agents which utilize different traveling modes, such as mass transport and individual vehicles, to perform activities. MATSim is able to calculate transportation flows in a given transportation network which includes spatial information on possible activities. The tool is able to determine possible road congestion and urban planning needs.

The data necessary for proper analysis consists of, in the case of power systems, the anticipation of future, non-vehicular electricity demand, detailed load and distribution network data, i.e., the region under investigation, as well as assumptions on possible charging locations and powers. MATSim requires information about the transportation and activity infrastructure, e.g., public transport, business, industry areas, including its Geographical Information System (GIS) data. Such information includes parking areas, which need to be identified, and their charging capacity. Assumptions concerning the initial composition of the vehicle fleet and their powertrains are crucial for VTAM. In order to calculate the vehicle’s energy consumption when have being used, appropriate drive cycles, giving a realistic picture of the driving behavior within the simulated area, e.g., city driving, need to be defined [61].

Figure 6.2: The integrated model comprising the Vehicle Technology Assessment Model (VTAM), the Multi Agent Transportation Simulation (MATSim) and the PEV Management and Power System Simulation (PMPSS).
6.2. Architecture and Functionality

6.2.2 Functionality

Drive cycles are used in individual vehicle simulations to determine energy consumption values of different vehicles on the roads for different average speeds. The consumption value is dependent on the chosen vehicle type, e.g., PEV or not, and its size. Based on the calculated values, energy consumption as a function of speed is determined using regression models. The functions, together with the technology fleet shares, are exported to MATSim using look-up tables as shown in Fig. 6.2. A consumption function is assigned to each agent in MATSim which is using a vehicle for transport. The function is assigned depending on the parameters of the utilized car, e.g., powertrain type. Subsequently, MATSim uses this information to calculate energy deployment and battery depletion levels considering the individually faced traffic situations. Obviously, the battery depletion levels are a crucial input to PMPSS.

MATSim simulates the transportation flows based on a reward optimization. The individual agents aim to pursue activities located in the transportation network. This network models the agents living environment. The activities are closely related to real life behavior and generate rewards for the agents. Using the detailed transportation demand of all agents, transportation flows are determined which are related to the agents’ activity schedules, such as work, leisure, shopping, the available parking lots and the charging areas. At the stage where transportation flows are simulated, MATSim uses the energy consumption models from the VTAM to calculate energy deployment and battery depletion levels considering the individually faced traffic situations. MATSim generates outputs which consist of

- arrival- and departure times,
- location of connection,
- power rating of the connection at the location,
- SOC at connection,
- desired SOC at departure and
- start- and end charging times.
Chapter 6. An Integrated Model for PEV Analysis

This output is transmitted to the PMPSS which simulates the underlying power system infrastructure incorporating PEV Managers [60, 96]. The managers are assigned to larger areas fed by transformers. As explained in Chapter 5, control price signals are generated in congestion cases. The signals encode the state of the power system [96] and can be returned to MATSim. The reward based optimization of the agents’ schedules can consider the signals and change the agents’ temporal and spatial charging and/or transportation behavior accordingly until network congestion is completely avoided. Then, the iterative system of MATSim and PMPSS is understood to be converged, i.e., behavioral and power system constraints are fulfilled.

6.2.3 VTAM - The vehicle technology assessment and fleet simulation

Vehicle fleet analysis

The dynamics of the car fleet are simulated using a bottom-up approach with a high disaggregation level. This allows to consider the market penetration of vehicles with alternative powertrains. The following powertrain categories can be considered:

- internal combustion engines (ICE),
- ICE-electric full hybrids with parallel configuration,
- ICE-electric plug-in hybrids with series configuration,
- electric motors with batteries (EV).

The energy is stored on board in form of gasoline or diesel and electricity. The differentiation includes several engine/motor power categories, different mass categories and the cohort of the vehicle’s construction year (yearly, starting from 1971). The car fleet composition is simulated using a survival probability of the cars which is calculated on the basis of dynamics observed between two subsequent years where each year a number of vehicles is replaced [137].

The database of the motor vehicles information system (MOFIS) of the swiss federal vehicle control bureau (EFKO) provides the input data
Figure 6.3: Vehicle fleet composition by powertrains in the future.

regarding the number of vehicles in each category for the particular starting year in order to calculate the survival probability. The penetration of new vehicles is based on an assumed market share development of the corresponding powertrain options. The observed trends towards hybridization, as well as growing market shares for diesel and gas vehicles, in the last years can be incorporated in the model according to [138]. Shares for both battery electric (EV) and PHEVs, are introduced using the S-shape penetration model for new products [137, 139, 140]. The S-shaped penetration of the vehicles in the fleet is illustrated by Fig. 6.3 [141].

Vehicles with an alternative powertrain, i.e., other than pure ICE, may have a different mass than an equivalent conventional car. Therefore, the distribution of new cars with alternative drive trains over weight categories has to be adjusted by taking into account the different weight of the powertrain and the batteries, etc. so that the structure of the cars’ size remains similar. Table F.1 in Appendix F shows the design parameters used for the fleet.

**Individual vehicle analysis**

The calculation of the individual energy consumption depends on the vehicle design, which is part of the fleet configuration, and on the driving behavior, modeled through driving cycles.
A library of vehicle models is built up according to possible combinations of vehicle design parameters. The parameters considered are powertrain, fuel and power types as well as weight. The parameters, given in Table F.1 in Appendix F, yield a combinatoric maximum of 1200 vehicle types which can be used in individual vehicle simulations. Hybrid and plug-in hybrid vehicles within the fleet are modeled with an additional energy management control strategy [142].

Vehicle energy consumption is strongly related to the driving behavior, the boundary conditions set by legal frameworks and the traffic situation on the road. The roads considered in the transportation network of MATSim are considered to allow a maximum speed equal to one of the following values: 30, 50, 60, 90, 120 km/h. The drive cycles are therefore adapted to these average speeds. The average speed on any road is a measure for road congestion [61].

The difference in energy demand between an ICE vehicle and an EV is exemplarily depicted in Fig. 6.4. The energy demand of the ICE is illustrated in Fig. 6.4(a) and the one of EV is shown in Fig. 6.4(b). The difference is obvious. The energy demand curves for different roads, i.e., different maximum speeds, vary for the conventional vehicle because of the varying efficiency of the gasoline engine. For the battery vehicle the energy demand curves approach each other as the energy recuperation strongly affects the overall energy demand strongly. With perfect recuperation efficiency, only the variability of the electric motor map would be pivotal [141].

Using the vehicle library and the driving cycles, specific energy consumptions [kWh/100km] for all vehicles over the different driving cycles are calculated using Newton’s second law and then represented through regression models [106]. Similar regression models can derived from the PEV energy hub model and are depicted in Chapter 4. Note that the regression models generated by VATM are based on more accurate vehicle models but the average consumption values are in the same range. In fact, the error of the depicted cases only exhibits a 10% deviation. In the case of PEVs, which incorporate two specific energy consumptions, i.e., charge depleting mode or hybrid mode, one regression model for electricity and one for gasoline consumption is used.
6.2. Architecture and Functionality

(a) Average energy consumption of a gasoline vehicle.

(b) Average energy consumption of a battery electric vehicle.

Figure 6.4: Example of the energy demand for different vehicles and different average driving velocities [141].
6.2.4 MATSim - The transportation simulation

Traffic can be modeled through the behavior of individual vehicles. Simulating each car as an individual agent is called agent based micro simulation and allows tracking of individual vehicles over time. Assigning a utility to each agent allows for individual decision modeling such as choosing the path to drive or choosing the location for refilling gasoline\(^1\).

MATSim [143] is an agent based transport simulation framework with focus on large scale scenarios, e.g., up to seven million agents and one million links, i.e., streets [144,145].

Figure 6.5 illustrates the simulation process deployed by MATSim. Each agent has a daily plan of trips and activities which it wants to perform. The activities include going to work, to school or going shopping. The daily plans, the network of streets and the facilities, which offer the activities, are modeled in the *initial demand*. The street network and the locations of facilities are unambiguously defined via the GIS [146].

Once the initial transportation demand of the agent population is determined, the plans are executed indicated through the box *simulation*. The result of the simulation is *scored* using an utility function. For example, an agent which arrived at work on time has a higher utility than an agent which arrived late. Working and other activities increase the agents’ utility while traveling decreases it. The goal of each agent is to maximize the total utility of its daily plan by *replanning* it accordingly. This *replanning* is based on a co-evolutionary algorithm [147]. Such an algorithm tries to find the maximum of a fitness function, in this case the utility function, using crossovers and mutations. In MATSim, the utility function has multiple degrees of freedom, such as the

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\(^1\)The utility which is meant here differs from the utility function described in Chapter 5. However, it also is based on the game theoretic concepts which are discussed in Chapter 5. The utility function used for demand management of the PEV agents can, however, be integrated into the utility concept of MATSim. This will be described later in this chapter.
6.2. Architecture and Functionality

routes, the time spent at work, the transportation mode, the locations visited and so on. The daily plans of the agents are evaluated and *bad* daily plans, i.e., plans with a low performance, respectively low utility, are deleted for each agent. This corresponds to survival of the fittest in co-evolutionary algorithms. Thereafter, new plans are generated based on the previous set of plans. The execution of all plans, their scoring and replanning is called a MATSim iteration. The complete simulation is an iterative process, which approaches a point of rest corresponding to an equilibrium. It is called *relaxed demand* [143]. Figure 6.6 shows a simulation result for the city of Zurich, Switzerland. The dots, each one representing one agent, are at different locations in the city, under different traffic situations. A traffic jam is indicated by the red dots.

Figure 6.6: This picture visualizes the location and speed of all agents in the middle of the city of Zurich, at around 6:30 in the morning. Agents colored in red have a low speed and are, compared to the free speed of the road, stuck in a traffic jam. Source: www.matsim.org.

One of the reasons for using an ABM approach for transportation simulation purposes is that individual agent preferences can be modeled. In order to evaluate constraints of the electricity network, detailed data on PEV location, time of connection and power demand are needed. Using high resolution road networks and including distinct buildings as well as particular activities allows for an accurate mapping between the transportation network and the electricity infrastructure.
6.2.5 The agent’s utility function in MATSim

The utility function used in MATSim is described in detail in [148]. It assigns a utility to the plan of each agent $k$ where

$$ k \in \mathcal{K} = \{1, 2, ..., K\} \quad (6.1) $$

It should be noted that, here, agent $k$ does not relate to the PEV agent $v$. It so far refers to the agent which is active in the MATSim environment performing activities and using various transportation modes. The relation between agent $k$ and PEV agent $v$ is introduced later in Section 6.2.6. The utility of agent $k$’s plan contains the utility $U_{k, \text{act}}$ for performing an activity $\text{act}$, where

$$ \text{act} \in \mathcal{A} = \{\text{home, work, education, leisure, shop...}\} \quad (6.2) $$

gives the set of all possible activities in the MATSim environment. Each agent $k$ has an individual set of activities which it would like to perform during the day. These activities are denoted by

$$ \mathcal{A}_k \subseteq \mathcal{A} \quad (6.3) $$

The subset $\mathcal{A}_k$ can be ordered through a function $f_1$ according to the time when the activity should be performed and according to the agent’s daily plan. This results in an activity plan $\mathcal{A}_k$ of agent $k$, where the function is given by

$$ f_1 : \mathcal{A}_k \to \mathcal{A}_k \quad (6.4) $$

with

$$ f_1(\mathcal{A}_k) := \{a \in \mathcal{A}_k | \exists \text{act} \in \mathcal{A}_k : f(\text{act}) = a\} \quad (6.5) $$

and

$$ a \in \mathcal{A}_k = \{1, 2, ..., N^\text{act}_k\} \quad (6.6) $$

Each activity of each agent $k$ is associated to a location within the MATSim environment, whereby the activity home of agent $k$ can but not necessarily has to be at a different location than the one of agent $k + 1$. The location of agent $k$’s activity $a$ is expressed as

$$ \text{loc}_{k, a} = \{x_{k, a}, y_{k, a}\} \quad (6.7) $$

where $x_{k, a}, y_{k, a}$ denote the GIS coordinates of the activity. All locations of the environment are contained in the set

$$ \mathcal{LOC} = \{\text{loc}_{k, a}...\} \forall a \in \mathcal{A}_k \land \forall k \in \mathcal{K} \quad (6.8) $$
The utility $U_{k,a}^{\text{act}}$ depends on the activity $a$, the starting time $t_{k,a}^{\text{start,act}}$ of the activity, its duration $t_{k,a}^{\text{dur}}$ but also on several other aspects such as if the agent $k$ arrived at a shop prior to its opening\(^2\). Such a case leads to a negative utility $U_{k,a}^{\text{wait}}$, since the agent needs to wait. Furthermore, if an agent starts working late $U_{k,a}^{\text{late,ar}}$ or departs too early from an activity $U_{k,a}^{\text{early,dp}}$, it will also be penalized. An activity may have a minimal duration so that the utility of the activity will be reduced if the duration is too short $U_{k,a}^{\text{short,dur}}$. The total utility of activity $a$ is expressed as

$$U_{k,a}^{\text{act}} = U_{k,a}^{\text{dur}} + U_{k,a}^{\text{wait}} + U_{k,a}^{\text{late,ar}} + U_{k,a}^{\text{early,dp}} + U_{k,a}^{\text{short,dur}}, \quad (6.9)$$

where the dependencies are omitted for shortness.

The total utility $U_{k}^{\text{plan}}$ of agent $k$’s daily plan also includes the (negative) utility of traveling from one activity to the next and is calculated according to

$$U_{k}^{\text{plan}} = \sum_{a=1}^{N_{k}^{\text{act}}} U_{k,a}^{\text{act}}(a, t_{k,a}^{\text{start,act}}, t_{k,a}^{\text{dur}}) + \sum_{a=2}^{N_{k}^{\text{act}}} U_{k,a}^{\text{trav}}(\text{loc}_{k,a-1}, \text{loc}_{k,a}) . \quad (6.10)$$

So far, the transportation model does not incorporate energy costs for traveling. In order to consider the energy cost in the agent’s daily plan, the utility function is extended by adding another term. The term $U_{k}^{\text{el.cost}}$ models the total energy costs of an agent. These costs depend on the amount of energy needed for traveling which is calculated using the regression function of the advanced vehicle models described in Section 6.2.3 or using the simple PEV energy hub modeling approach found in Chapter 4, the activity plan and the driving patterns. The term $U_{k}^{\text{el.cost}}$ reduces the agent’s utility $U_{k}^{\text{plan}}$ given in (6.10). The total energy cost during the day is composed of charging costs $U_{k,a}^{\text{charge}}(T, \text{loc}_{a})$ incurred at all activity locations of agent $k$. It is expressed as

$$U_{k}^{\text{el.cost}} = \sum_{a=1}^{N_{k}^{\text{act}}} \sum_{T = f_{2}(t_{k,a}^{\text{end,act}})} f_{2}(t_{k,a}^{\text{start,act}}) U_{k,a}^{\text{charging}}(T, \text{loc}_{k,a}) , \quad (6.11)$$

\(^2\)Note that $U_{k,act}^{\text{act}} \neq U_{k,a}^{\text{act}}$. The variable $U_{k,act}^{\text{act}}$ denotes the utility value of some activity $\text{act} \in \mathcal{A}$, in general. This is in contrast to the variable $U_{k,a}^{\text{act}}$ which denotes the utility of activity $a$ in the agent’s specific daily plan.
where $t_{k,a}^{\text{start,act}}$ and $t_{k,a}^{\text{end,act}}$ denote the starting and ending time of activity $a$ in continuous time notation. The function $f_2$ transforms continuous time into discrete time steps $T = \{1,...,N_{\text{time}}\}$.

The individual cost terms $U_{k,a}^{\text{charging}}(T,loc_{k,a})$ are calculated from the energy consumption at a certain location which is multiplied by the electricity price $\psi(T)$ during that time step\(^3\), as given by

$$U_{k,a}^{\text{charging}}(T,loc_{k,a}) = \psi(T)p_{k,n}(T)\Delta t_{k,a}^{\text{charging}}(T,loc_{k,a}) ,$$

$$\Delta t_{k,a}^{\text{charging}}(T,loc_{k,a}) = t_{k,a}^{\text{end,charge}}(T,loc_{k,a}) - t_{k,a}^{\text{start,charge}}(T,loc_{k,a}) ,$$

(6.12)

where $\Delta t_{k,a}^{\text{charging}}(T,loc_{k,a})$ is the charging time at $loc_{k,a}$ and in time step $T$. The charging time is defined by the start and end times $t_{k,a}^{\text{start,charge}}(T,loc_{k,a})$ and $t_{k,a}^{\text{end,charge}}(T,loc_{k,a})$, respectively. The variable $p_{k,n}(T)$ denotes the charging power of agent $k$ at electricity network node $n$ in time step $T$.

### 6.2.6 The PEV and power system simulation

The demand management approach for PEVs, which is elaborated in Chapter 5, can be used to map agents from the MATSim environment to the power system model and the developed PEV management approach without having to switch to another framework than multi agent theory. The subset of the set of agents $\mathcal{K}$, which uses PEVs to travel to particular activity locations and which connects the vehicles in an area supervised by one PEV Manager, can be translated into a set of PEV agents $\mathcal{V}_n$. In mathematical terms, the subset of agents using PEVs, which are aggregated by one PEV Manager, is denoted

$$m \in \mathcal{M}_n = \{1, 2, ..., M_n\}$$

(6.13)

where $\mathcal{M}_n$ can be translated to the set of managed PEV agents, given in (5.1), according to

$$f_3 : \mathcal{M}_n \to \mathcal{V}_n(T) ,$$

(6.14)

\(^3\)The electricity price $\psi(t)$ should not be mixed up with the control price signal $\pi_n(T, \theta(T)|\Theta_n(T))$ determined by the PEV demand management scheme. Here, as a first step, it is assumed that $\psi(T)$ is an exogenously given electricity price, i.e., a time of use electricity price or a real time electricity price.
with

\[ f_3(\mathcal{M}_n) := \{ v \in \mathcal{V}_n(T) | \exists m \in \mathcal{M}_n : f_3(m) = v \} \]  \hspace{1cm} (6.15)

Using this relation, the set of PEVs managed at one node \( n \) in an electricity network is a subset of the complete set of agents which are active in MATSim, i.e.,

\[ \mathcal{V}_n(T) \subseteq \mathcal{K} \]  \hspace{1cm} (6.16)

In this way, the three independent tools are linked to form one, integrated tool. The transportation agents are directly related to power system agents, i.e., PEV agents that compete for a potentially scarce resource. Thus, agent technology is used to model both, the transportation and the power systems.

### 6.3 Examples using the Integrated Model

The integrated model can be utilized in two different setups to investigate the impacts of wide scale PEV adoption. One possibility is to neglect the feedback information signal from PMPSS to MATSim. Then, the information on the spatial and temporal distribution of congestion in the electricity network is not available to MATSim. This assumes that the transportation equilibrium is not altered, even though PEV load is postponed or shed by PEV Managers at certain nodes.

Different insights are provided by the results of the transportation simulation. Not considering an information feedback allows to determine typical PEV load patterns. These patterns could evolve in uncontrolled charging scenarios. Considering the actions of the PEV Managers results in a differing load curve, which then assumes no pattern change in transportation behavior although behavioral constraints might be violated. These load patterns take into account people’s daily behavior as well as the charging/refuelling options offered by the infrastructure of the area under investigation.

The second possibility of utilizing the integrated model incorporates the feedback of network congestion information to MATSim via PMPSS signals. In this case, MATSim can include this information in the daily behavior of agents and penalize situations which would lead to congestion of the electricity infrastructure. This might, however, change the former
Figure 6.7: Uncontrolled charging of PEVs using a constant electricity price and a generic test fleet. Home and work locations are considered as charging spots, only. The utilized electricity network is depicted in Fig. 5.6 in Chapter 5.5.

transportation equilibrium, i.e., the agents choose different routes, locations or even transportation modes in order to avoid electricity network congestions. In a way, such setup can be considered realistic. It seems obvious that human beings would alter their behavior after experiencing several times that their PEV has not been charged as desired.

6.3.1 No feedback from PMPSS to MATSim

A test case is used in the following to illustrate results of the integrated model without using a possible information feedback from PMPSS to MATSim. The test case uses the four node system which is already described in Chapter 5.5; see Fig. 5.6. However, the utilized MATSim data differs in the following examples from the one in Chapter 5.5. Here, the transportation system comprises 28’000 streets, 16’000 agents and the activities "home", "work", "education" and "shopping". Several streets are mapped to one node. Node 1 represents the largest area with a big number of streets and thus activities. Node 4 is the smallest area. Generic transformer ratings of 9.4 MVA, 4.4 MVA, 8 MVA and 8.2 MVA are chosen, respectively. The energy consumption while driving is simulated using the model elaborated in Chapter 4.
6.3. Examples using the Integrated Model

The result of the MATSim charging schedule in its relaxed state, i.e., in its equilibrium, is depicted in Fig. 6.7. It shows the uncontrolled PEV load imposed on the test system. It is assumed that the vehicles can be charged at their home and at their work activity locations. In accordance with the scheme described in (6.11)–(6.12), a constant energy price throughout the day is given to MATSim. Therefore, the agents simply charge as soon as they arrive at their respective destination. Two load peaks, of up to 30 MW, occur when the agents charge in uncontrolled manner at arrival upon their locations, that is at 08:30 in the morning, as well as at their home locations, that is at 17:00. The contribution of node 1 to the load peaks is the largest because its share of activity locations is also the largest.

The result of the PEV Manager optimizations within PMPSS is depicted in Fig. 6.8. The figure depicts the control price signals at each node. They are determined by a PEV Manager optimization according to Chapter 5.3. The optimization scheme considers a base loading of the electricity system. This load cannot be controlled. It is inflexible and exhibits load curves of household or business areas. It partly loads the transformers which are feeding the respective areas. The PEV Manager optimization uses the transformer rating as constraints for each PEV Manager. The constraints ensure that the remaining power difference between transformer rating and base loading is distributed to the connected vehicles.
Figure 6.9: Uncontrolled charging of PEVs using a dual electricity price tariff, a generic test fleet, home and work as charging locations and the electricity network given in Fig. 5.6 in Chapter 5.5.

Figure 6.8 shows two PMPSS signal peaks for node 1. The relatively high control price peaks indicate a large load, e.g., a depleted fleet trying to attain large amounts of energy thereby congesting this transformer. The 8:30 peak at node 2 indicates a congestion at this node as well. The fleet at node 2 is less numerous than the one at node 1 while also having a higher average SOC. Therefore, the total flexible demand at node 2 is lower, as can be concluded from the explanations given in Chapter 5.2 and Chapter 5.3. The PEV Managers shift, due to the generated control price signals, excessive load to later time intervals. However, the load shift performed by the PEV Managers is not depicted here. Only the load as imposed by the MATSim result is shown.

Figure 6.9 illustrates the impact of a variable electricity price on the PEV load. Here, a dual time of use tariff is chosen. The price is fed to MATSim according to (6.11)–(6.12). The high price period lasts from 06:00 to 21:00. Thereafter, the low price period starts. Instead of two peaks of about the same size, one large load peak of about 55 MW can be seen at 21:00. This is due to the electricity price falling from the high value to the lower value at 21:00. As all agents know this in advance, they almost simultaneously start to charge during the low price period. Only a small share of charging is performed during the high price time, e.g., at around 09:00. The agents which choose to charge during this time are not able to reach their next activity location without charging. Hence, they have to connect and consume electricity at a high price.
6.3.2 Information feedback from PMPSS to MATSim

In order to avoid congestion of the electricity infrastructure the integrated model offers to feed back the PMPSS control price signal to MATSim which should result in a different agent behavior. However, it is found that feeding only the control price signal back to MATSim is not sufficient since the signal does not contain information on the charging potential of other time steps, i.e., how much power is available in other time steps.

Transmitting only the signals which are depicted in Fig. 6.8 to MATSim results in an agent behavior, in which the agents will charge 30 minutes earlier but still with the same degree of simultaneity. When using the feedback option for the second time, i.e., during the third MATSim simulation, the agents behave as in the first MATSim simulation and the electricity load profile looks exactly as shown in Fig. 6.7. This alternating behavior of the agents is due to missing information of the charging potential in other time steps. In MATSim, only the electricity price signal generated by PMPSS is used to inform the agents which time step is favorable for charging and which is not. Transmitting a flat electricity price signal for the not congested times and a high price for the congested ones, results in this binary behavior. The agents will try to avoid the congestion, however, since no preference for charging in other times steps is given to them, they will select the next possible one.

Including information on the anticipated free capacity of a transformer to charge PEVs when transmitting the control price signal to MATSim allows to distribute the PEV load over several time steps. This can decrease load peaks and avoid network congestion. It is achieved by an agent charging scheduler.

The agent charging scheduler

One option to implement a centralized approach is to integrate a smart charging scheduler between MATSim and PMPSS. The scheduler has the possibility to react to information available from MATSim as well as from PMPSS. Therefore, the entity knows arrival and departure times of every agent as well as the SOC required at departure for the agent to be
able to travel to the next location in an all electric mode. Furthermore, the scheduler receives the nodal control price signals, the daily energy prices and the base load in the particular area of each manager. The information is encoded in the form of

\[
\psi_n(T) = \begin{cases} 
\pi_n(T) - 1 + \frac{L_n(T)}{P_{n,\text{max}}(T)} & \text{if } \sum_{v \in V_n(T)} p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) < P_{n,\text{max}}(T) \\
\pi_n(T, \Theta_n(T)) & \text{if } \sum_{v \in V_n(T)} p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) = P_{n,\text{max}}(T) \
\forall n \in \mathcal{N}.
\end{cases}
\] (6.17)

In non-congested times, the first part of (6.17) is valid. Then, a signal \(\psi_n(T)\) is transmitted to MATSim incorporating the information of the current exogenous price signal \(\pi_n(T)\) superimposed with the actual loading \(L_n(T)\) rated in relation to the maximal suppliable power \(P_{n,\text{max}}(T)\). In case the node is congested, the control price signal is determined by the optimization of the PEV Manager given in (5.14)–(5.15). Note that \(\psi_n(T)\) is now modified in contrary to (6.12).

The scheduler’s objective is to avoid network congestion and to ensure that the agents are able to attain their desired SOC. Hence, the smart scheduler avoids situations where connected PEVs could potentially compete for the scarce resource, i.e., power. Thereby, the smart scheduler prevents that PMPSS and MATSim deliver differing charging schedules and thus different agent behaviors. In fact, the smart scheduler ensures compliance with the predetermined daily activity plans and desired battery energy levels. The complete, integrated method actively incorporates real time energy prices when determining the agent’s daily utility in relation to all other potential gains through activities. The scheduling is achieved by minimizing an objective function given as

\[
f_2(t^{\text{end,act}}_{v,a}) = \sum_{T=f_2(t^{\text{start,act}}_{v,a})}^\infty \sum_{n=1}^N \sum_{v=1}^{N_v(T)} \sum_{a=1}^{N_{\text{act}}(T)} \psi_n(T, loc_{v,a})p_{v,n}(T)\Delta t_{v,a}^{\text{charge}}(T, loc_{v,a}),
\] (6.18)

with

\[
\Delta t_{v,a}^{\text{charge}}(T, loc_{v,a}) = t_{v,a}^{\text{end,charge}}(T, loc_{v,a}) - t_{v,a}^{\text{start,charge}}(T, loc_{a}),
\] (6.19)

is subject to
6.3. Examples using the Integrated Model

\[ p_{v,a}^{\min} \leq p_{v,a}(\cdot) \leq p_{v,a}^{\max}, \quad (6.20a) \]
\[ T - 1 \leq t_{\text{start.charge}}(\cdot) \leq T, \quad (6.20b) \]
\[ t_{\text{start.act}}^{v,a} \leq t_{\text{start.charge}}(\cdot) \leq t_{\text{end.charge}}(\cdot), \quad (6.20c) \]
\[ t_{\text{start.charge}}(\cdot) \leq t_{\text{end.charge}}(\cdot) \leq t_{\text{end.act}}(\cdot), \quad (6.20d) \]
\[ 0 \leq \sum_{T=t_{\text{start.act}}^{v,a}}^{t_{\text{end.act}}^{v,a}} p_{v,a}(\cdot) \Delta t_{\text{charge}}(\cdot) \leq DOD_{v,a}(\cdot), \quad (6.20f) \]
\[ 0 \leq \sum_{T=t_{\text{start.act}}^{v,a}}^{t_{\text{end.act}}^{v,a}} \Delta t_{\text{charge}}(\cdot) \leq t_{\text{dur}}^{v,a}, \quad (6.20g) \]

where the dependencies are omitted for shortness.

The function sums over all nodes of the system, over the connected PEVs, over the activities available at the nodes and over the time intervals during which the activities are being performed. The summands incorporate the value of the control price signal for every agent \( v \), which utilizes and connects a PEV as well as performs activity \( a \) at location \( \text{loc}_{v,a} \) of node \( n \) in time interval \( T \). The control price signal is multiplied by the power connection of the PEV \( v \) and the charging time interval \( t_{\text{charge}}^{v,a}(T,\text{loc}_{v,a}) \) in order to calculate the cost of acquired energy.

The charging time in time interval \( T \) is determined by (6.19). The charging time is the difference between the charging end time \( t_{\text{end.charge}}^{v,a}(T,\text{loc}_{v,a}) \) and the charging start time \( t_{\text{start.charge}}^{v,a}(T,\text{loc}_{v,a}) \). The constraints of the smart scheduling algorithm include the physical power connection limits of the PEVs in (6.20a). Further, the scheduler is designed such that the charging start time can be flexibly chosen within an interval \( T \) as stated by (6.20b). However, the charging start time must always lie before the charging end time. Both need to lie in the same interval as expressed in (6.20c). Clearly, the charging start times must always lie within the activity duration length (6.20d) just as the charging end times as denoted in (6.20e). The total energy consumed cannot exceed the initial depth of discharge \( DOD_{v,a}(t_{\text{start.act}}^{v,a},\text{loc}_{v,a}) \) at arrival as denoted in (6.20f). Finally, the total charging time must always sum up to a value lower than or equal to the duration time of the activity \( t_{\text{dur}}^{v,a} \) as stated in (6.20g).
Utilizing the agent charging scheduler

Figure 6.10 depicts the charging behavior of the agents when using the integrated model with the option of information exchange and the agent charging scheduler. The figure illustrates how the load is distributed more evenly throughout the day by the agent grid scheduler. In comparison to the earlier case, where charging is uncontrolled, the load peak is substantially reduced to a maximum of 4.8 MW. This is only 16.7\% of the previous amount. Note the reduced scale of the ordinate in Fig. 6.10. Although convergence is not inherent for such an iterative setup, a stable equilibrium of the transportation and charging behavior is reached within 7 iterations for this example. The equilibrium represents a situation in which all PEV agents attain enough energy to reach their next location while fulfilling their daily plan.

The iterative scheme takes into account the daily load curve of the system. The curve is not depicted, but consists a relatively high load in the evening hours between 18:00 and 23:00 with a peak at 22:30. The inverse of the load shape can be conjectured in the charging behavior of the agents. The PEV load is high during times when the base load is low, e.g., between 01:00 and 06:00. During times when the base load is high, e.g., between 18:00 and 22:00, the PEV load is low. The information on
6.4. Mapping Transportation with Electricity Networks

Figure 6.11: Evolution of the control price signals, determined by the PEV Managers in the four node test network. The price signals are plotted for 4 subsequent iterations.

the system loading is included in the signal transmitted from PMPSS to MATSim [61].

Figure 6.11 illustrates the evolution of the control price signal at the heavily loaded node 1 from one iteration to the next. The first four iterations are shown. It can be seen that the PMPSS control price signals decrease from iteration to iteration due to rescheduling of PEVs. The system evolves towards an equilibrium, i.e., an agent behavior, where individual activity plans, desired energy levels and mobility constraints imposed on the large agent population are fully taken into account.

6.4 Integrating the Metropolitan Area Electricity Distribution with the Transportation Network

So far, the integrated tool of power and transportation systems utilized a simple four node electricity system. However, the tool can be adapted to investigate the impacts of electric mobility on real electricity and transportation systems. To this end, detailed data is necessary. For the power system, data of the metropolitan area of Zurich, Switzerland is
used. The electricity grid data of this area comprises several voltage levels including a 380 kV network, the 150 kV network intra metropolitan high voltage network and the 11/22 kV intra urban distribution network. Lower voltage levels are not considered. The nodes at the 11/22 kV level are referred to as

$$n \in \mathcal{N} = \{1, 2, \ldots, N\}$$  \hspace{1cm} (6.21)

where

$$\text{loc}_n = \{x_n, y_n\}$$  \hspace{1cm} (6.22)

gives the GIS coordinates of the electric node, i.e., of the transformer station. Nodes at the 11/22kV level are clustered in zones. The zones are fed from transformers installed at the 150 kV level. Each transformer at this level feeds several nodes all belonging to a single zone. The zones are not connected to each other and are subsequently denoted

$$z \in \mathcal{Z} = \{1, 2, \ldots, Z\}$$  \hspace{1cm} (6.23)

where each zone is made up of nodes

$$n_z \in \mathcal{N}_z = \{1, 2, \ldots, N_z^{\text{zone}}\}$$  \hspace{1cm} (6.24)

and

$$\mathcal{N}_1 \cup \mathcal{N}_2 \cup \ldots \cup \mathcal{N}_Z = \mathcal{N}$$  \hspace{1cm} (6.25)

The complete 11 kV and 22 kV network of the metropolitan area is depicted in Fig. 6.12. The different zones are not depicted in the figure.

For the purpose of integrating the transportation and the power system network, GIS coordinates of activity locations $\text{loc}_{k,a}$, i.e., street coordinates, are clustered according to their proximity to the network nodes. This means that coordinates of several activity locations are assigned to the node which models the load for the particular activity area. The mapping is expressed as a function

$$f_4 : \mathcal{LOC} \to \mathcal{N}$$  \hspace{1cm} (6.26)

with

$$f_4(\mathcal{LOC}) := \{n \in \mathcal{N} | \exists \text{loc}_{k,a} \in \mathcal{LOC} : f_4(\text{loc}_{k,a}) = n\}$$  \hspace{1cm} (6.27)

Using this relation, each agent, which uses a PEV and which connects it at an activity location in the MATSim environment, is unambiguously mapped to one node of the power system of the metropolitan area. The agent can quit the activity and leave using a different transportation mode, e.g., walking or public transport. This is, however, not important for the setup considered here, as only the location where the PEV is
Figure 6.12: 11 kV and 22 kV electricity distribution network of the metropolitan area of Zurich, Switzerland.

connected is considered in PMPSS. Thus, the agent can perform several activities in MATSim while its car stays connected to one charging spot. A PEV Manager is assigned to each load node in the 11 kV and 22 kV network. Figure 6.12 illustrates this.

The hierarchical demand management, which is developed in Chapter 5, is applied to the metropolitan area electricity distribution system. The 150 kV network, depicted in Appendix G in Fig. G.1, is furnished with S-PEV Managers at every 150 kV transformer. Each transformer supplies one 11 kV or 22 kV zone. Figure 6.13 illustrates this integration of the S-PEV Manager in the 150 kV network. Each transformer, connected to the 150 kV network, is equipped with one S-PEV Manager. The S-PEV Manager supervises the PEV Managers in its zone $z$, ac-
Chapter 6. An Integrated Model for PEV Analysis

Figure 6.13: Integration of S-PEV Managers into the distribution network of a metropolitan area.

cording to the derivation given in Chapter 5. In the figure, one S-PEV Manager supervises one 11 kV zone and two other S-PEV Managers manage two 22 kV zones, respectively. Furthermore, each zone incorporates several PEV Managers. The S-PEV Managers ensure that the 150 kV transformers, which supply large areas, are not overloaded and that the voltages in the zones are kept in acceptable ranges. Obviously, the hierarchical management approach can be extended to the 380 kV network which is not performed in this work.

6.5 Case Studies using the PEV Demand Management Approach in the Metropolitan Area of Zurich

Figure 6.14 shows three scenarios defined and used to investigate the impact of electric mobility on the transportation and electricity infrastructure of Zurich. They are referred to as Scenario A, Scenario B and Scenario C, are explained below, and incorporate the years 2010, 2020, 2035 and 2050. The year 2010 is referred to as the base case. In the base case no PEVs are apparent.

Parking spots are modeled for each urban area. The capacity of the parking spots is dependent on the current urban planning situation. The
6.5. Case Studies

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Year</th>
<th>Market Penetration</th>
<th>Charging Infrastructure</th>
<th>Maximum Driving Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>A: «Low»</td>
<td>2010</td>
<td>/</td>
<td>/</td>
<td>/</td>
</tr>
<tr>
<td></td>
<td>2020</td>
<td>3.5 kW</td>
<td>/</td>
<td>80 km</td>
</tr>
<tr>
<td></td>
<td>2020</td>
<td>3.5 kW</td>
<td>/</td>
<td>80 km</td>
</tr>
<tr>
<td></td>
<td>2050</td>
<td>3.5 kW</td>
<td>/</td>
<td>150 km</td>
</tr>
<tr>
<td>B: «Medium»</td>
<td>2010</td>
<td>/</td>
<td>/</td>
<td>/</td>
</tr>
<tr>
<td></td>
<td>2020</td>
<td>3.5 kW 11 kW</td>
<td>/</td>
<td>80 km</td>
</tr>
<tr>
<td></td>
<td>2050</td>
<td>3.5 kW 11 kW</td>
<td>/</td>
<td>80 km</td>
</tr>
<tr>
<td>C: «High»</td>
<td>2010</td>
<td>/</td>
<td>/</td>
<td>/</td>
</tr>
<tr>
<td></td>
<td>2020</td>
<td>3.5 kW 3.5 kW 3.5 kW</td>
<td>/</td>
<td>80 km</td>
</tr>
<tr>
<td></td>
<td>2050</td>
<td>11 kW 11 kW 11 kW 11 kW</td>
<td>/</td>
<td>150 km</td>
</tr>
</tbody>
</table>

Figure 6.14: Description of studied scenarios for large electric mobility penetration into the individual vehicle fleet.

Capacities are incorporated in the MATSim environment. Dependent on the scenario and the particular year which is simulated, the parking spots can feature different charging options, i.e., charging capacities. MATSim is used to simulate the agent behavior of the Canton Zurich in order to capture commuting behavior. In total, a fleet of 1’000’000 vehicles is simulated.

Scenario A models a relatively low penetration of PEVs, i.e., a pessimistic development of electric mobility, assuming that only one phase charging spots are available at the home locations in the transportation network. The battery sizes change throughout the years. They grow in their maximum range from 80 km in 2020 to 150 km in 2050.

Scenario B conjectures a medium penetration of PEVs. Here, three phase charging options, i.e., a connection capacities of 11 kW, are assumed at all at work locations. Home locations are left with the one phase charging option, i.e., 3.5 kW. Scenario B is not shown in the following as it models situation bin between Scenario A and Scenario C.. The results and an analysis can be found in [141].
Chapter 6. An Integrated Model for PEV Analysis

<table>
<thead>
<tr>
<th>Year</th>
<th>EV</th>
<th>PHEV</th>
<th>P-HEV &amp; ICE</th>
</tr>
</thead>
<tbody>
<tr>
<td>2020</td>
<td>1.5%</td>
<td>8.8%</td>
<td>89.7%</td>
</tr>
<tr>
<td>2035</td>
<td>13.1%</td>
<td>54.7%</td>
<td>32.2%</td>
</tr>
<tr>
<td>2050</td>
<td>37.8%</td>
<td>60.7%</td>
<td>1.5%</td>
</tr>
</tbody>
</table>

Table 6.1: Share of vehicle types in the scenarios used for the analysis of electric mobility impacts.

Scenario C models a high penetration of PEVs in the vehicle fleet. Pervasive charging options are assumed, i.e., PEVs are able to charge virtually everywhere. The charging power and the battery sizes vary according to the simulated year. The assumptions made are found in Fig. 6.14. In the following, Scenario A and Scenario C are discussed detail.

The vehicles’ energy consumption is simulated through the VTAM. Detailed model in formation and results are found in [141]. The PEVs feature different driving efficiencies in the years simulated. The efficiencies include an efficiency improvement factor which increases the efficiency 1 % per year. In Scenario A, the PEVs feature an average energy consumption of about 0.16 kWh/km. As efficiency increases, the average consumptions decreases to about 0.13 kWh/km. In Scenario C similar numbers are found. The average energy consumption there decreases from 0.19 kWh/km to about 0.15 kWh/km. The evolution of the average energy consumption is found in [141]. Such consumption values are low compared to former case studies, i.e., [149]. The latter case studies utilized a consumption of about 0.5 kWh/km. The vehicle fleet in the following case studies drives up to 26’000’000 km using electricity. Thus, on average, each car drives 26 km per day. Table 6.1 gives a comprehensive overview of the vehicle type shares for two scenarios.

Zurich’s base load is determined through a cumulated load growth model given by

\[ L(y) = L(2003)(1+g)^{(y-2003)} \forall y \geq 2003, \]  

where \( L(y) \) refers to the base load of the year to be simulated, \( L(2003) \) is Zurich’ aggregated load measured by the local utility in the year 2003 and \( g \) is the load growth factor. In the following, \( g \) is set to 1 %.

No detailed information is available on the load fed by the transformers on the 11 kV and 22 kV level and its temporal evolution. A snapshot of the respective transformer peak load available for the year 2003 is used.
to calculate the load share of the particular transformer on the aggregated city peak load. The share is used to determine the temporal load evolution at each node throughout the day. To this end, it is assumed that the load contribution of the particular transformer on the total load of the city stays constant. The proportionality factor is used to calculate the load at each time step by multiplying the total city load with this factor. The rating of each transformer station on the 11 kV and 22 kV voltage level is also not known. As a reasonable assumption, the rating is chosen such that the peak load at the particular transformer station only loads the transformer to 60 %. The simulated time step size $T$ is chosen to be 15 minutes.

In order to study the effects on the current electricity system, the system’s infrastructure dimensioning and topology is based on the year 2010. The electric mobility scenarios and transportation simulations utilize the power system of 2010.

Scenario A and Scenario C are used to investigate the impacts of uncontrolled PEV charging first. In a second step, the electricity infrastructure is furnished with PEV Managers as discussed in the foregoing sections. This proceeding allows to directly compare the effects of controlled charging. The maximum allowed loading per transformer station, i.e., per PEV Manager, is set to 100 %.

### 6.5.1 Impacts of uncontrolled PEV charging on the metropolitan area distribution system of Zurich

To investigate the effects of large scale electric mobility on the electricity infrastructure as it is designed, dimensioned and operated nowadays, simulations are performed without any charging control. The vehicles are assumed to connected as soon as they arrive at a location where charging is possible. They charge until their battery reaches 80 % SOC. They are not charged until 100 % because such a high energy level in the battery decreases the life time of the battery. This is prevented by the battery energy management installed in the car. The capacity of the battery is chosen according to the desired driving range of the vehicle.
Scenario A

Scenario A models a scenario which is understood as a pessimistic, home charging only scenario. Figure 6.15 shows the number of parked PEVs in the city of Zurich for the years 2020, 2035 and 2050. In 2020, the maximum number of connected PEVs in Zurich is smaller than 10'000. However, the maximum number increases substantially for the years 2035 and 2050. In 2050, a maximum of about 120’000 PEVs is connected at 03:00 at night. The evolution of the number of parked PEVs reflects the fact that the cars are only able to connect at home location. Therefore, the maximum of connected PEVs appears during late night hours and the minimum is found around 10:30 in the morning, when most people are at work. A little increase in connected PEVs is noticed around 13:00. This is due to agents which chose to drive home during lunch hours.

Figure 6.16 shows the number of parked PEVs at each node of the 11 kV and 22 kV electricity distribution network of Zurich throughout the whole day. It can be seen that in 2020 a maximum of about 80 PEVs is parked at 24:00. In general, in 2020, the number of parked PEVs in the city is small. The plateaus, seen in Fig. 6.16(a), indicate that no PEVs are connected to or disconnected from the particular node for a prolonged time interval, i.e., no PEVs arrive in or leave the area supplied by this transformer station.
6.5. Case Studies

(a) Number of parked PEVs throughout the day at each node of the distribution system of the city of Zurich, Scenario A, year 2020.

(b) Number of parked PEVs throughout the day at each node of the distribution system of the city of Zurich, Scenario A, year 2035.

(c) Number of parked PEVs throughout the day at each node of the distribution system of the city of Zurich, Scenario A, year 2050.

Figure 6.16: Number of parked PEVs at each node of the distribution system of the city of Zurich throughout the day; Scenario A, and the years 2020, 2035 and 2050.
Figure 6.17: Uncontrolled PEV load in the city of Zurich in Scenario A, the years 2020, 2035 and 2050.

In 2035 and 2050, more PEVs connect to the system. Figure 6.16(c) exhibits a maximum of about 1350 PEVs parked at around 03:00 at night in the city. This coincides temporally with the maximum number of parked PEVs found in the Fig. 6.15. The three dimensional plot reveals nodes of the electricity distribution system which are most affected by PEV activity in this scenario. Here, nodes dominated by a residential structure stand out.

Figure 6.17 shows the load imposed on the system by the fleet of electric vehicles which charges in an uncontrolled manner. It can be seen that a maximum load of about 3 MW is added to the system at around 19:30 in the year 2020 due to uncontrolled charging. In total, 26.7 MWh per day are consumed by the PEV fleet in 2020. The maximum load imposed increases substantially for the year 2035 and 2050. In total, 237.3 MWh per day are consumed by the PEV fleet in the year 2035.

In 2050, a maximum load of about 33 MW are imposed at around 18:15. The load peak is introduced by a large number of agents that return home from their daily activities and connect the PEVs to charge them. The peak is due to the load aggregation effect of the electric vehicle fleet while charging. The peak decreases to 19 MW until 22:00. The minimum load is found around 7:30 in the morning. Then, many agents are either on their way to an activity location or their PEVs are fully charged after have been parked for the whole night. The load at this
time, i.e., at 07:30, is not zero. A small number of agents is active and returns home, e.g. after a night shift. In total, 342.4 MWh per day are consumed in the city by PEVs in the year 2050.

Figure 6.18 shows the uncontrolled PEV load at each node in the city’s MV distribution network throughout the day. The maximum load in 2020 found at one node is rarely higher than 0.1 MW. This is due to the low simultaneity of connecting PEVs and the small aggregation effect of the load. As few PEVs connect, the simultaneity remains low in the year 2020. Additionally, the PEVs are often fully charged before the next PEVs connects. A large portion of PEVs arrives with a relatively high energy level. They only need one or two time steps, i.e., 30 minutes, to be fully charged. Hence, the aggregation of the load also remains small. This is also due to the high efficiency of the cars.

The situation, however, changes for the years 2035 and 2050. More and more load is introduced through an increased number of PEVs. Therefore, more load peaks are generated. Expectably, the nodes which feature the highest number of PEVs also exhibit the highest load peaks. The load peaks grow to about 0.5 MW in 2050. They appear during times when the electricity infrastructure of Zurich is already heavily loaded, i.e., during 18:00 and 20:00. This additional load could stress a transformer substation because the rating of these substations often lies between 1 MW and several MWs. Load valley hours can also easily be observed in the plot. They appear between 05:00 and 08:00.

The spiky load behavior in 2050 is due to many PEVs which arrive with a fairly high SOC at charging locations. After connection, the vehicles are charged rather fast and the load decreases thereafter until the next PEVs connects. Hence, the aggregation effect when charging remains low but is certainly bigger than in the year 2020. The battery energy level of the vehicles is high at arrival. This has several reasons. The cars do not travel far, they feature a very high efficiency when driving and they recuperate energy.
Chapter 6. An Integrated Model for PEV Analysis

(a) PEV charging power demand throughout the day at each node of the distribution system of the city of Zurich, Scenario A, year 2020.

(b) PEV charging power demand throughout the day at each node of the distribution system of the city of Zurich, Scenario A, year 2035.

(c) PEV charging power demand throughout the day at each node of the distribution system of the city of Zurich, Scenario A, year 2050.

Figure 6.18: Uncontrolled PEV power demand throughout the day at each node of the distribution system of the city of Zurich; Scenario A, and the years 2020, 2035 and 2050.
Figure 6.19 shows the resulting aggregated load curve of the city of Zurich for the different years. For the year 2020 the difference between the base case of 2010 and the PEV case can barely be noticed. The maximum PEV load added is less than 1 % of Zurich’s peak load in the base case. The shape of Zurich’s load curve changes with more PEVs being connected and charged. In this uncontrolled scenario the PEVs aggravate the second load peak of the base case load curve which appears at 18:00. In 2050, this load peak is increased from about 550 MW to about 570 MW, which corresponds to about 4 % growth in peak load. A small increase of the first load peak is noticed. It increases from about 550 MW to about 560 MW. This corresponds to a 2 % load growth.

Figure 6.20 illustrates the evolution of the 150 kV transformer loading over the years 2020, 2035 and 2050 at peak load time. In the base case, two transformers are loaded more than 80 %, two transformers are loaded more than 75 % while the other 28 transformers on the 150 kV voltage level are loaded around 60 % or less. The loading barely changes in the year 2020. A higher impact of electric mobility is seen in the year 2050. Then, the loading of all transformers increases several percentage points. Two transformers are loaded a bit less than 90 % and two are loaded around 80 %. Other transformers exhibit a loading of around 60 %.
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Figure 6.20: Loading of 150 kV transformers in the city of Zurich at peak load, i.e., 18:15, for uncontrolled PEV charging; Scenario A, years 2020, 2035, 2050.

(a) Load of the 150 kV transformer substations in the city of Zurich at 18:15, Scenario A, year 2020.

(b) Load of the 150 kV transformer substations in the city of Zurich at 18:15, Scenario A, year 2035.

(c) Load of the 150 kV transformer substations in the city of Zurich at 18:15, Scenario A, year 2050.
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In such a PEV penetration scenario no active charging control would be necessary to mitigate undesired effects such as overloading or excessively low voltages. A simple expansion of the network in the appropriate areas would be sufficient to accommodate large scale electric mobility. Therefore, the controlled charging case, which would focus on the mitigation of network challenges is waived at this point. The interested reader can find results in [141].

Scenario C

Scenario C models a high penetration of PEVs into the vehicle fleet and consequently into the electricity system. Figure 6.21 shows the evolution of the number of parked PEVs in the city of Zurich throughout the day. In 2020, about 25’000 PEVs are parked at maximum and about 10’000 at minimum. The number increases substantially until 2050 when, at maximum, more than 225’000 PEVs are parked in the city at around 15:00. The graphs exhibit the expected connectivity behavior for this scenario as charging is allowed at every activity location, i.e., at home, at work and at public areas. The number of parked and connected PEVs reaches its minimum during nighttime when 150’000 are connected at 03:00. Thus, a substantial number of agents, which use PEVs, commute into the city in order to perform their work activities. Note that in 2050 on average, about 20% of the simulated fleet is parked and connected in Zurich.
When compared with Scenario A, this scenario features much more electric vehicles. While the maximum number of connected PEVs is 120,000 in Scenario A, the number is almost doubled here. Note that the connectivity behavior is altered and hence this scenario affects the electricity system differently than Scenario A.

Figure 6.22 illustrates the number of connected PEVs at each node of the city’s MV distribution system throughout the day. In the year 2020 the number of connected cars is substantially increased for almost every node in the system when compared with Scenario A. Over the years, the number of connected cars grows. In 2050, up to about 3,500 PEVs connect at one single node. This is more than double the number found in Scenario A. Two nodes exhibit such high numbers of parked PEVs. Investigating the data more closely, it is found that these nodes are on the outskirts of the inner city of Zurich. There, many parking spots are modeled to be available. Coincidentally in this scenario, all these parking spots feature charging options. The agents choose to park the PEVs somewhat further away from the city center and charge the cars there. They may use other transport options to travel into the city center.

In general, the three dimensional plots reveal nodes which are dominated by business and leisure activity locations as these nodes exhibit the appropriate charging infrastructure in this scenario. However, the nodes are also strongly affected by the parking, charging and commuting options in this scenario. Two nodes exhibit a so called park and ride behavior of the agents. Note that the parking behavior at the nodes differs strongly from the one of Scenario A. Nodes which reveal a residential parking behavior exhibit a comparably lower number of parked PEVs than at other nodes.

Figure 6.23 shows the uncontrolled load introduced by the PEV fleet of Scenario C. The maximum load introduced by the PEVs in 2020 is around 8 MW at 09:30 in the morning. In total 95.6 MWh are consumed by the fleet. The maximum load in 2020 of Scenario C is already higher than in Scenario A for the same year. For the years 2035 and 2050 the load increases substantially. In 2035, a total of 643.8 MWh are consumed by the PEVs and a peak load of about 63 MW is introduced to the system.
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(a) Number of parked PEVs throughout the day at each node of the distribution system in the city of Zurich, Scenario C, year 2020.

(b) Number of parked PEVs throughout the day at each node of the distribution system in the city of Zurich, Scenario C, year 2035.

(c) Number of parked PEVs throughout the day at each node of the distribution system in the city of Zurich, Scenario C, year 2050.

Figure 6.22: Number of parked PEVs at each node of the distribution system in the city of Zurich throughout the day; Scenario C, and the years 2020, 2035 and 2050.
Figure 6.23: Uncontrolled PEV load in the city of Zurich in Scenario C, for the years 2020, 2035 and 2050.

In 2050, 824.3 MWh are consumed and the maximum load imposed by the uncontrolled charging of the PEVs is around 77 MW at 08:30 in the morning. The PEV load stays relatively high throughout the day. After the first peak in the morning a load plateau of around 42 MW appears until around 18:00. The PEV load decreases thereafter to about 10 MW and below during night time.

The load shape is caused by the transportation and connectivity behavior of the agents. Most of the agents arrive in the city in the morning in order to perform their work activities. The large load peak in the morning is caused by the degree of simultaneity with which the agents arrive and connect in the city. As expected, the load peak starts to grow from 05:00 in the morning when the first agents arrive in the city. At 08:00 most of the agents already arrived in the city and connected their cars. Note that normal working hours start at around 08:30.

The plateau later during the day is caused by agents that either start to work late, e.g., in the afternoon or evening, or which perform shopping or leisure activities. Since many more charging spots are available, the agents take advantage of them and charge during the day in the city. The load decreases in the evening to 12 MW, half of the load found in Scenario A. This proves that the commuting behavior overlaps the agent behavior observed in Scenario A, where the agents charge the cars at their home locations. The high charging capacity in this scenario
prevents that load adds up to higher values. As the charging capacity is limited to 3.5 kW in Scenario A, the load aggregation effect is bigger.

However, an overall load peak of about 80 MW is not particularly big for a PEV fleet of up to 225,000. This is due to the high efficiency of the PEVs in the year 2050. Although this fleet drives about 5,000,000 km, the overall energy consumption is only about 750 MWh. A charging efficiency of 90% is used. Therefore, more than 800 MWh are consumed.

Figure 6.24 shows the uncontrolled PEV load at each node of Zurich’s MV distribution system throughout the day. A spiky load shape is evident in the three dimensional plot of the load in the year 2020. The aggregated PEV load shape, illustrated in Fig. 6.23, is in accordance with the load shapes given for the individual nodes in Fig. 6.24(a). The highest load peaks are found in the morning at nodes where a large number of PEVs is parked. The load peaks in 2020 already reach values which are as high as 0.3 MW. This is comparable with the size of the load peaks seen in Scenario A in the year 2050. The maximum of a single load peak grows until the year 2050 to about 3 MW.

The load shape at the nodes differs from each each other although the parking behavior is similar at numerous nodes in the electricity system. This is due to the differing SOC of the individual cars and the different connectivity behavior. Obviously, one node reveals a particularly high simultaneity of agents connecting their PEVs which, additionally, incorporate a comparatively low SOC. Since the SOC is low, the aggregation effect of the PEV load is larger and a load peak of up to 3 MW appears.

Figure 6.25 shows the effect of the PEV load on the aggregated load curve of the city. For the year 2020, the impact of PEVs can barely be seen. However, the loading at some individual nodes is already high, a prove that the impact of PEVs on the electricity distribution system will be mostly a spatially limited one.

The load curve of Zurich is substantially altered until 2050. The load peak is shifted away from midday and evening hours to the morning hours. The load peak in Zurich in 2050 coincides with the load peak of the PEV load for this year. The simulated load curve exhibits a peak load plateau in the morning hours, i.e., 08:30 until 12:00. For uncontrolled charging, the load is barely increased during the evening and night hours. The peak load of the city is now found to by 600 MW.
Figure 6.24: Uncontrolled PEV charging power demand throughout the day at each node in the distribution system of the city of Zurich; Scenario C, for the years 2020, 2035 and 2050.
Figure 6.25: Zurich load in Scenario C; the years 2020, 2035 and 2050.

Figure 6.26 shows a snapshot of the loading of the electricity system on the 11 kV and the 22 kV network level in the year 2050 during the peak load at 10:00. In contrast to Scenario A, it is noticed that the 11 kV and 22 kV network level faces challenges. An asset colored in a violet color illustrates an overload. It should be noted that overload refers to a situation where the load of one asset, here it is a transformer, exceeds the maximum rating of the asset. An indication of overload does not contain information on how much the maximum rating of the assets is violated. For example, a loading of 100.1 % is called an overload just as a loading of 150 %.

In specific, transformers on this voltage level are subject to being overloaded by PEV charging. Two overloads are spotted near the city center, to the north of the lake. However, the overloads do not only concentrate in the city center. This could be expected as business, i.e., work, locations now feature charging opportunities. Three overloads are observed in the Northwest of the city. The transformers are to be loaded on average to 30 % of their rating. Some are loaded up to 70 %. Noticeably, no electricity distribution lines are overloaded. Most of them stay around a 30 % load level. A plot of the electricity line loading during peak load time in the year 2050 is found in Appendix H in Fig. H.4.
Figure 6.26: Asset loading in the city of Zurich on the 11 kV and the 22 kV voltage level at 10:00 for uncontrolled PEV charging in Scenario C, year 2050.

Figure 6.27 shows the number of overloads caused by excessive PEV charging in the electricity network throughout the day for the different years investigated. In the year 2020 no overloads are detected and therefore no figure for this year is given. In the year 2035, displayed in Fig. 6.27(a), a small number of transformer overloads is found. Noticeably, most of the overloads appear in the morning when the PEV load grows fast and the agent connectivity behavior exhibits a high simultaneity. Up to 6 overloads appear between 07:00 and 10:00. The number of overloads decreases later in the day. The number of transformer overloads corresponds roughly to 0.5% of the transformers installed in the city.

In the year 2050, illustrated in Fig. 6.27(b), more transformer overloads appear. Obviously, this is caused by the increased number of charging PEVs. At 08:30 the largest number of transformer overloads is detected; in total 10 overloads. This coincides temporally with the appearance of the PEV load peak. The number of transformer overloads corresponds to about 1.5% of the installed transformers.
Later during the day the number of overloads decreases. On average about 4 transformers are overloaded during the day until about 18:00. This corresponds to about 0.5 % of the installed transformers. Obviously, enough capacity is available during night time for the fleet.

Figure 6.28 shows a snapshot of the loading of electricity network on the 150 kV voltage level at peak load for the year 2050. The 150 kV network level does not face overloads, neither during the peak time nor some time else. However, all assets exhibit a higher maximum loading than in Scenario A. Numerous transformers are heavily loaded. Some
Figure 6.28: Asset loading in the city of Zurich on the 150 kV voltage level at 10:00 for uncontrolled PEV charging in Scenario C, year 2050.

are even loaded as high as about 90 %. These transformers are located close to the city center.

The additional load of PEVs stresses not necessarily only assets on low voltage levels which feed spatially limited areas. The challenges also do not concentrate on areas which are already heavily loaded. The challenges for the electricity system are highly distributed and strongly correlate with the transportation and connection behavior of the agents. The aggregation of the PEV load affects also assets on higher network levels which incorporate a rather high capacity.

Figure 6.29 shows a snapshot of the the 150 kV transformer loading at peak load for the different years. As expected, in 2020, barely any impact of PEV load on these assets can be seen. This is similar to Scenario A although the overall peak load introduced by the PEVs is substantially higher in Scenario C. The PEV load is spatially distributed, i.e., between numerous transformers. Large effects, and therefore the difference to Scenario A, are more obvious for the years 2035 and 2050. In 2050, all transformers on the 150 kV level face a substantially higher load than in the base case of 2010. Four transformers are loaded more than 80 % and three more than 70 %. 18 out of the 32 transformers face a loading which is higher than 60 %.
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(a) Load of the 150 kV transformer substations in the distribution system of the city of Zurich at 10:00, Scenario C, year 2020.

(b) Load of the 150 kV transformer substations in the distribution system of the city of Zurich at 10:00, Scenario C, year 2035.

(c) Load of the 150 kV transformer substations in the distribution system of the city of Zurich at 10:00, Scenario C, year 2050.

Figure 6.29: Loading of 150 kV transformers in the distribution system of the city of Zurich at peak load, i.e., 10:00, for uncontrolled PEV charging; Scenario C, years 2020, 2035, 2050.
Figures illustrating the loading of the 150 kV lines are found in Appendix H, in Fig. H.5. It can be seen that the 150 kV lines are far from being overloaded. Figure H.6, also found in Appendix H, shows the loading of four transformers on the 380 kV and 220 kV network level for the years 2020, 2035 and 2050. These transformers face a remarkable load increase which contrasts Scenario A. However, they are far from being endangered by potential overloads caused by PEV charging.

6.5.2 Effects of controlled PEV charging in the metropolitan area distribution system of Zurich

The challenges for the distribution grid remain small in Scenario C but controlled charging helps to solve them without costly, invasive and grid expansion. For the controlled scheme the operational state description, described in Chapter 3, is used. Vehicles, which cannot remain in the controlled charging mode are transferred to the uncontrolled charging mode so that they can attain their desired SOC before departure. This is done one time step ahead of the time instant where they have to transfer in any case. In case a node should be congested by a fleet in uncontrolled charging mode, the available capacity is divided between the cars in the uncontrolled mode.

Furthermore, several parameters of the PEV demand management need to be set before performing studies utilizing the demand management scheme and demonstrating its effects.

The parameter $\alpha_{v,n}(T)$ is set constant and to a value of 42.8 Rp/kWh, which corresponds to the current gasoline price weighted by the motor efficiencies. This choice allows the integration of day ahead energy prices in the management. If the exogenous electricity price should exceed this value, an agent would not chose to charge its car, unless it is an EV, and it is forced to charge in order reach the desired SOC at departure. This is in accordance with the discussion found in Section 5.2.2 and Section 5.2.3.

The parameter $\beta_{v,n}(T)$ is also chosen to be constant and to a value of 19.25 Rp/kWh. The exogenous control price signal is chosen to be constant throughout the day and set at a value of 12 Rp/kWh, for simplicity. The choice of $\beta_{v,n}(T)$ ensures that the PEVs could be charged until 80 % of SOC. Setting the minimum SOC to 30 % gives that the PEVs are potentially charged until 100 %. This is prohibited by the charging
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Figure 6.30: Controlled PEV load in the city of Zurich; Scenario C, the years 2020, 2035 and 2050.

constraints of the PEV Manager and the fact that PEVs transfer into the Stand By state once they reached their desired SOC. The exponent $h$ in the energy valuation function, illustrated in Fig. 5.1, is set to 2.

Scenario C

Figure 6.30 shows the PEV load for controlled charging in Scenario C. The graphs of the different years look very similar to the graphs of the uncontrolled scenario. For the year 2020, no difference is found as no load is temporally shifted. The PEV load curves for the year 2035 and 2050 are different to the ones depicted for the uncontrolled case in Fig. 6.23. The main difference, which can be noticed in the year 2050, is that the overall load peak is reduced. In the uncontrolled case, the load peak exceeds 77 MW. Here, the maximum PEV load reaches only 71 MW. Some load is shifted to later times when the electricity distribution system incorporates more capacity to supply the PEV demand. However, some load cannot be served. Figure 6.31 illustrates the load shifting.

In total, 95.6 MWh, 643.6 MWh and 821.9 MWh are consumed by the PEV fleets in 2020, 2035 and 2050, respectively. Comparing these values with the ones given in Section 6.5.1, differences of 0.2 MWh and 2.4 MWh are found for the years 2035 and 2050, respectively. This difference is due to the fact that some nodes are congested for extensive
Figure 6.31: Difference between uncontrolled and controlled PEV load. A positive deviation indicates the uncontrolled PEV load to be bigger than the controlled PEV load. Load shifting in the city of Zurich is thus indicated; Scenario C, the years 2020, 2035 and 2050.

time periods. This prohibits PEVs to attain their desired SOC before departure. Even having implemented the uncontrolled mode in this case study does not solve this issue. Some PEVs have to leave with a lower SOC.

Figure 6.32 shows the controlled PEV load at all nodes of the MV distribution system throughout the day. The PEV load in 2020 shows many load spikes but their height is relatively low. Comparing it with the uncontrolled case, given in Fig. 6.24(a), it is observed that the control does not affect the PEV load at the nodes in this year. Figure 6.32(b) illustrates the controlled PEV load in the year 2035. Here, besides load peaks which can reach up to 2 MW, load plateaus can be seen at different load levels. These load plateaus indicate congested transformers on the 11 kV and 22 kV voltage level. They are protected by PEV Managers. One example is node 733.

The number and the size of the load plateaus grows until the year 2050. This indicates that more transformers reach their maximum loading for prolonged times. Note that not only transformer can causes such load plateaus. The hierarchical control could introduce load plateaus, i.e., reduce the load at uncongested transformers, due to congestion of transformers at higher voltage levels or to excessively low voltages on the 150 kV network level. However, this is not the case in this scenario, as will be shown later in other figures.
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(a) PEV charging power demand throughout the day at each node of the distribution system of the city of Zurich, Scenario C, year 2020.

(b) PEV charging power demand throughout the day at each node of the distribution system of the city of Zurich, Scenario C, year 2035.

(c) PEV charging power demand throughout the day at each node of the distribution system of the city of Zurich, Scenario C, year 2050.

Figure 6.32: Controlled PEV charging power demand throughout the day at each node of the distribution system of the city of Zurich; Scenario C, the years 2020, 2035, 2050.
At node 733 in Fig. 6.32(c), it can be seen that the PEV load is relatively high, about 0.9 MW during night time, i.e., at around 22:00. However, the load plateau during the day is found only at around 0.7 MW. Other load peaks can be found at night which are somewhat higher than the load plateaus during the day at the same node. This phenomenon is due to the base load of the system, i.e., the inflexible load at the transformers which varies over time. The base load is low during the night. Hence, the PEV Managers feature more available power which can be distributed to the PEVs. During the daytime, when the base load is higher, the power which can be distributed to PEVs is smaller. Hence, the load peaks vary in size throughout the day and can be sometimes higher than the load plateaus.

When comparing Fig. 6.32(c) with the load in the uncontrolled case shown in Fig. 6.24(c), it is obvious that the load peaks are significantly decreased. The load peaks in the uncontrolled case are as high as 3 MW while in the controlled case the highest peak is found to be 1.75 MW. This is a load reduction of about 50%. The charging control reduces the peaks and distributes the power over longer times. A high simultaneity in charging is counteracted by the control approach taking advantage of as much temporal charging flexibility as possible.

The difference in overall energy consumption can be better understood when investigating Fig. 6.32(c) in detail. The load plateaus at some nodes are apparent for very long times. These are also the nodes which feature many PEVs. The capacity constraint at these nodes introduces a difference in overall energy consumption because the large number of vehicles congests the node for a long time and limits the energy which can be drawn, even when taking advantage of the full charging flexibility of the vehicles. There are two solutions to this issue. Either, the capacity of the transformer is increased at these nodes or the vehicle load is not only shifted temporally but also spatially, i.e., to other nodes.
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(a) Control price signals throughout the day at each node of the distribution system of the city of Zurich, Scenario C, year 2020.

(b) Control price signals throughout the day at each node of the distribution system of the city of Zurich, Scenario C, year 2035.

(c) Control price signals throughout the day at each node of the distribution system of the city of Zurich, Scenario C, year 2050.

Figure 6.33: Control price signals throughout the day at each node of the distribution system of the city of Zurich; Scenario C, the years 2020, 2035 and 2050.
Figure 6.33 shows the control price signals for the different years of Scenario C. As mentioned, no control price signal appears in Fig 6.33(a) because the network does not face congestions in 2020. However, in the year 2035, the PEV Managers generate control price signals in order to temporally shift PEV load and avoid overloads. Many, temporally extended control price signals at almost the highest possible price signal value of 42.8 Rp/kWh are found during the day time. This is due to a large number of agents which connect their PEVs at work locations and introduce additional load to an already heavily loaded system. Hence, transformers face congestion and PEV Managers are activated. They distribute the available capacity to the large number of agents. Other nodes exhibit low control price signals which last a couple or even only one time step. In such cases, the PEV Manager shifts load, which would otherwise overload the transformer for one or two time steps, to later times taking advantage of the available charging flexibility of the PEVs.

During night time, no control price signals are generated. This is due to a large amount of available capacity which can be used to charge the PEVs. However, there could be cases where the transformers are congested for some time intervals. Depending on the load situation at a specific node, PEVs can stress the network even during night time. However, such effect is spatially limited and strongly depends on the given scenario. In [149] a similar scenario but with a higher average energy consumption of the vehicles introduced congestion even during the night time. Thus, statements that electric mobility will not introduce congestion if the cars are charged during night time are not necessarily valid.

Obviously, more control price signals peaks appear throughout the simulated years. This is an indication for more system congestion. However, when investigating closely Fig. 6.33, it is observed that a number of price signal peaks changes the temporal appearance, which is due to the general trend of more and longer network congestions.

Figure 6.34 shows the load curve of Zurich for different years of Scenario C for the controlled case. While in the year 2020 no big difference between base load and the load including PEVs can be seen, the impact of PEVs is easily noticed for the year 2035 and 2050. In comparison with the uncontrolled case illustrated in Fig. 6.25, the load curve for the controlled case is similar. The maximum load in the controlled scenario is also found to be 650 MW. The load which is shifted is barely noticeable here. Not much load is shifted into the evening or night hours. As many
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agents connect and charge their vehicles in order to commute home, the energy of these vehicles must be received during the day.

Figure H.11 Appendix H shows a snapshot of the 11 kV and the 22 kV network at 10:00 in the year 2050. No overloads can be found. However, there are transformers which are loaded to their maximum rating. The general load situation, i.e., the coloring of the network assets, differs largely from the one given Fig. 6.26. This is due to the charging control which postpones load. Red dots, i.e., overloads, are not detected. As PEV load is temporally shifted, assets are loaded differently. A detailed illustration of the line loading on the 11 kV and 22 kV voltage level is found in Appendix H in Fig. H.7. The load situation on the 150 kV network level is not illustrated as it is similar to the uncontrolled case.

A detailed illustration of the transformer load level is found in Fig. H.9 in Appendix H for the different years of Scenario C. It is similar to the uncontrolled case. No voltage bound violations are found in this scenario. As no 150 kV transformers or voltage bounds are violated, the supervisory manager is not activated and the load plateaus, illustrated in Fig. 6.32 are caused only by PEV Managers active in the 11 kV and 22 kV voltage level. Detailed information on line loadings during the peak load hour for the different years are found in Appendix H in Fig. H.8. Also, a plot of the transformer loading at the 380 kV voltage level is found in Fig. H.10.
Comparison of Uncontrolled and Controlled Charging using Low Efficiency PEVs in Scenario C

So far, the electric vehicle fleet is modeled to be highly efficient. External effects, such as bad weather conditions, are not considered. However, these effects can have a substantial influence on the energy consumption of the electric vehicles. In order to illustrate these effects, Scenario C is simulated with the same vehicle fleet as used before but with a doubled energy consumption. Additionally, the technology improvement per year is set only to 0.5% which represents a pessimistic technological evolution of electric mobility. The charging capacity of all parking and charging options in the city is set to the 3.5 kW instead of 11 kW.

Figure 6.35 shows the PEV load of Scenario C in the year 2050 for low efficiency PEVs in the uncontrolled and in the controlled case, respectively. The peak load is about 148 MW without active control and about 134 MW with active control. The reduction of the peak load is about 10%. The load is partly shifted into the evening and night hours. However, since a lot of power is demanded during the day and spatial charging flexibility is not included in the setup, some load has to be shed.

In the uncontrolled case 1764.4 MWh are consumed. In the controlled
A positive deviation indicates the uncontrolled PEV load to be bigger than the controlled PEV load. Load shifting in the city of Zurich is thus indicated; Scenario C, the year 2050 and low efficiency PEVs.

case, 1727.5 MWh are consumed by the fleet leaving 36.8 MWh of unserved PEV load. This is due to the fact that PEV load can only be temporally shifted. A spatial load shift, i.e., shifting unserved load from one heavily congested location in the inner city to a not congested location in the outskirts later in the day is not allowed here. Figure 6.36 illustrates the load shift performed by the algorithm.

Figure 6.37 shows, for comparison reasons, the uncontrolled and controlled PEV load at the nodes of the distribution system throughout the day as well as the control price signals generated by the demand management algorithm. Figure 6.37(a) shows the uncontrolled PEV load. Load peaks up to 5 MW are observable. This is more than double as high as observed before in the simulation of the good case of Scenario C. Many load peaks are substantially increased. The load at the individual nodes does not exhibit such a spiky shape as seen in Fig. 6.32 because the charging simultaneity is much higher in this scenario. The PEV load aggregates as the PEV charging is temporarily extended. Thus, higher load peaks are formed.
Chapter 6. An Integrated Model for PEV Analysis

(a) Uncontrolled PEV charging power demand throughout the day at each node in the distribution system of the city of Zurich, Scenario C, year 2050.

(b) Controlled PEV charging power demand throughout the day at each node in the distribution system of the city of Zurich, Scenario C, year 2050.

(c) Control price signals throughout the day at each node of the distribution system of the city of Zurich; Scenario C, year 2050.

Figure 6.37: Uncontrolled, controlled PEV power demand control price signals throughout the day at each node in the distribution system of Zurich, Scenario C, year 2050.
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Figure 6.38: Number of overloaded transformers for uncontrolled PEV charging in Scenario C, year 2050.

Figure 6.37(b) shows the controlled PEV load. Note the different color coding. The overall load level is significantly decreased. The largest load at one node is found to be about 1.5 MW. Also, a large number of load plateaus can be seen. Be reminded that these plateaus indicate congestions. Many nodes are congested for extensive periods which last until the evening and night hours. The control approach shifts excessive demand to later times. Postponing charging activities results into a higher charging simultaneity as additional PEVs connect later in the day and compete with the already parked PEVs for power. Note that in case an excessive number of PEVs are in the uncontrolled charging state, the capacity of the transformer is proportionally divided between them. In such a case, the flexibility of the PEVs in the controlled charging state is fully exploited and they are switched off.

Figure 6.37(c) illustrates the control price signals in the network. A high degree of network congestion is observable as many nodes exhibit high control price signals. Price signals of 42.8 Rp/kWh indicate a transformer congestion by PEVs in the uncontrolled charging state. Minor, temporarily very limited congestions are also noticed in the morning between 08:00 and 10:00. Furthermore, congestions are also seen in the late evening and night hours, i.e., even after 00:00. This is due to the load shift performed by the PEV Managers. Before, large, excessive demands and hence a high overloads caused the PEV load to be supplied as fast as possible, leaving much capacity unused in the evening hours. With activated charging control, this is not the case anymore. Then, the transformer capacity is considered as the load limit at the nodes and
the capacity is distributed between the connected PEVs. As soon as the load of PEVs in the uncontrolled charging state has to be curtailed due to an excessive number of PEVs in this state, a load shedding takes place. This is responsible for the difference in energy consumption between the uncontrolled charging case and the controlled charging case. However, many areas, i.e., nodes, do not exhibit congestion at all. Thus, asset stress due to PEV charging is a spatially limited effect.

Figure 6.38 illustrates the number of transformer overloads in the network when the PEVs are charged in an uncontrolled manner. At maximum, 24 overloads appear, which corresponds to about 3% of the installed transformers. On average, between 07:00 and 20:00, about 10 transformers are constantly overloaded. Note again, that the amount of overload is not indicated here.

Figure 6.39 shows the aggregate load curves of Zurich for the uncontrolled and controlled case. The difference between the uncontrolled and the controlled case is easily noticeable here, especially in the morning hours when the peak load is decreased. The peak load in the uncontrolled case is about 675 MW while for the controlled case it is about 660 MW. Note that the morning peak is much more increased compared with the former simulation of Scenario C. A load plateau during most of the day is not apparent anymore. The figure emphasizes how important assumptions on the electric car efficiency and driving behavior
The city’s load situation changed vigorously. The load is substantially increased. The energy demand of the fleet in this scenario is about 17.5% of the city’s energy demand in 2010. The losses at peak load hour account to about 8 MW for the PEV fleet which gives about 2 MWh during the peak load time, i.e., 10:00. This gives about 5.5% increased PEV load due to losses over the network levels considered here.

Finally, Fig. 6.40 shows the load situation on the 11 kV and 22 kV network level in the city for the uncontrolled charging case. Overloaded transformers are indicated by the violet color. The overloads do not concentrate in the city center. Some overloads are located in the center and other are located in the outskirts of the city in the Northwest and in the East. The appearance of transformer overloads is hence strongly dependent on the parking capacity of the areas, the agents’ transportation behavior and on the already apparent base loading of the particular assets. The electricity lines are far from being heavily loaded. Many lines are colored in green which indicates a loading of under 30% of their overall rating.
Figures showing line and transformer loadings on the 11 kV, 22 kV, 150 kV and 380 kV network level are found in Appendix I for the controlled charging case. The uncontrolled charging case is not depicted as the asset loading is similar. In the figures it can be observed that a peak load time no lines at the 11 kV and the 22 kV network level are close to their maximum rating, the same is noticed for the lines on the 150 kV network level. However, a large number of lines faces a substantial load increase.

The transformers on the 150 kV level also face a substantial load increase. Four transformers almost reach their maximum load level. Note that one transformer is actually overloaded half an hour before peak load time. This is not seen for the peak load time due to the inhomogeneous temporal connectivity behavior of PEVs. One transformer on the 380 kV network level is overloaded. PEV Managers, which could avoid this, are not installed at this voltage level.

6.6 Concluding Remarks

This chapter interconnects the energy consumption model for individual PEVs of Chapter 4 and the agent based PEV demand management method of Chapter 5. A mathematical framework is derived integrating these approaches. Finally, an integrated, agent based model of vehicle, transportation and power systems is developed to analyze the effects of large scale electric mobility on power systems.

Two possible integration options are highlighted. One without information feedback from the PEV demand management scheme to the transportation simulation and one with feedback. The latter features an agent charging scheduler which is able to schedule the charging behavior of individual vehicles temporally and spatially.

The utilization of the smart charging scheduler is computationally expensive. Thus, the PEV demand management approach without information feedback is used to perform large scale case studies in the distribution network of Zurich, Switzerland. The case studies concentrate on two scenarios. One represents an optimistic evolution of electric mobility until the year 2050, i.e., many PEVs on the streets until 2050, and the other a pessimistic evolution. The scenarios are used to show effects
of uncontrolled charging and of controlled charging of the vehicle fleet in the distribution network.

Uncontrolled charging leads to undesired effects, such as overloading of assets. Several scenarios illustrate these effects. The controlled charging approach aims at mitigating these effects, thus avoiding overloads by taking advantage of the PEV charging flexibility. The case studies show that no overloads appear when activating the demand management scheme. In the latter case, about the same amount of energy is consumed but the temporal distribution of energy consumption is altered. As an additional effect, some PEVs can leave without having received the desired amount of energy. The reason for this is that spatially limited congestions of the distribution network are severe. Even when taking full advantage of the available charging flexibility, it is not possible to resolve some capacity congestions and thus to ensure that all PEVs attain their desired SOC at departure. Hence, grid expansion in certain areas seems unavoidable if charging is not to be shifted spatially. The integrated tool offers an analysis method to locate areas highly probable to face congestion in the future.

The used scenarios feature both, highly efficient PEVs and PEVs with low efficiency. The results are strongly influenced by the vehicle efficiency and the kilometers driven. Utilizing PEVs with a higher energy consumption, i.e., lower efficiency, leads to substantially higher challenges for distribution networks. This is shown in the last case study. Such higher energy consumption could easily appear and be related to bad weather conditions, such as high temperatures, rain or snow. Asset overloading is then more probable, also on higher network levels. This definitely will call for intelligent charging methods.

A general rule relating energy consumption, peak load and the number of PEVs could not be found. In Scenario A, a peak load of 33 MW is caused by about 70'000 PEVs. In the good case of Scenario C, a peak load of 77 MW is caused by 200'000 PEVs and in the bad case of Scenario C a peak load of 142 MW is caused by the same number of PEVs. Many variables, such as average energy consumption when driving, available charging capacity, driven distance and connectivity behavior influence the overall PEV peak load.
Chapter 7

Providing Vehicle to Grid (V2G) Services with a large Fleet of PEVs

This chapter describes how a large number of PEVs, which are distributed over a large distribution network and which are connected in V2G mode, can be aggregated to form a controllable storage of substantial size. The aggregation considers the approaches discussed in the previous chapters. The storage is controlled by a centralized controller which utilizes model predictive control (MPC). This control approach allows to balance the fluctuating generation of Renewable Energy Sources (RES) taking into account the uncertainty introduced by the mobility of the individual cars. The temporally varying power rating and energy capacity of the aggregated storage as well as the fluctuating generation are incorporated in a prediction error which is an input to the model. Finally, a case study is performed. It uses the distribution system of Zurich, Switzerland and a transportation simulation. The case study illustrates that large numbers of PEVs are able to balance large amounts of RES even if the physical limitations of the distribution network are considered.
7.1 The Aggregation of PEVs for V2G Services in a large Electricity Network

The integrated model for the PEV impact analysis, which is described in the last Chapter, can be also used for an analysis of network impacts introduced by the provision of V2G services. As described in Chapter 3, V2G technology is, among other things, envisioned to balance fluctuating infeed of RES [9, 25, 101, 102] or to provide ancillary services, such as primary, secondary or tertiary control, to power systems [57, 136, 150, 151]. Since the integrated model at hand provides detailed temporal and spatial information on PEV behavior as well as on the network state, a vehicle aggregation scheme is developed which takes behavioral and grid limitations into account.

The aggregated storage incorporates a maximum and a minimum power output which is dependent on the PEV fleet contracted for V2G service and on the current state of the distribution network. The maximum and minimum power of the storage is calculated by

\[ P_{\text{V2G}}^{\text{min}}(T) = \sum_{n=1}^{N} \left\{ \begin{array}{ll}
N_n^V(T) \sum_{v=1}^{p_{\text{V2G},v,n}^{\text{min}}(T)} & \text{if } \sum_{v=1}^{N_n^V(T)} p_{\text{V2G},v,n}^{\text{min}}(T) > P_{\text{V2G},n}^{\text{min}}(T), \\
P_{\text{V2G},n}^{\text{min}}(T) & \text{if } \sum_{v=1}^{N_n^V(T)} p_{\text{V2G},v,n}^{\text{min}}(T) < P_{\text{V2G},n}^{\text{min}}(T),
\end{array} \right. \]

(7.1)

\[ P_{\text{V2G}}^{\text{max}}(T) = \sum_{n=1}^{N} \left\{ \begin{array}{ll}
N_n^V(T) \sum_{v=1}^{p_{\text{V2G},v,n}^{\text{max}}(T)} & \text{if } \sum_{v=1}^{N_n^V(T)} p_{\text{V2G},v,n}^{\text{max}}(T) < P_{\text{V2G},n}^{\text{max}}(T), \\
P_{\text{V2G},n}^{\text{max}}(T) & \text{if } \sum_{v=1}^{N_n^V(T)} p_{\text{V2G},v,n}^{\text{max}}(T) > P_{\text{V2G},n}^{\text{max}}(T),
\end{array} \right. \]

(7.2)

with

\[ P_{\text{V2G},n}^{\text{min}}(T) = -L_n(T), \]

\[ P_{\text{V2G},n}^{\text{max}}(T) = P_{\text{trafo},n}^{\text{max}} - \sum_{v=1}^{N_n^V} p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) - L_n(T). \]

(7.3)
The controllable power rating of the aggregated storage is defined by the upper bound $P_{\text{V2G}}^{\text{max}}(T)$ and by the lower bound $P_{\text{V2G}}^{\text{min}}(T)$. The upper bound gives the maximum power with which the storage can be charged while the minimum bound gives the maximum power with which the storage can be discharged.

The aggregated storage is modeled by summing over all distribution system nodes and over the vehicles which are connected to the particular node, as denoted in (7.1) and (7.2). Furthermore, the aggregation scheme considers the maximum and minimum physical power which can be scheduled at a particular node. These are given by $P_{\text{V2G},n}^{\text{max}}(T)$ and $P_{\text{V2G},n}^{\text{min}}(T)$ in (7.3). The variables ensure that the power fed in by the vehicles does not exceed the load at the node or, if the vehicles should consume power, the transformer rating. Certainly, it cannot exceed the maximum or minimum total available power of all connected vehicle. Hence, the contribution of a particular node in the network to the aggregated storage is limited by its transformer capacity, the load at the time step and the total available control power offered by the connected vehicles.

The power ratings of the aggregated PEV storage do not necessarily have to be symmetric. One reason for that is the individually limited contribution of the nodes in the network. Another reason is the differing contribution of the PEV. For example, in the case of a PEV incorporating a fully charged battery and a one phase connection, the maximum power for discharging is -3.5 kW. The maximum power for charging is 0 kW, because the vehicle is fully charged and cannot be charged any further.

The energy contained in the aggregated PEV storage in relative terms is calculated by

$$E_{\text{V2G}}^{\text{rel}}(T) = \frac{\sum_{n=1}^{N} \sum_{v=1}^{N_n(T)} e_{\text{V2G},v,n}(T)}{\sum_{n=1}^{N} \sum_{v=1}^{N_n(T)} C_{v,n}}$$

(7.4)

where $e_{\text{V2G},v,n}(T)$ denotes the absolute energy in kWh contained in the battery of PEV $v$ at node $n$. The energy is given in relative terms as (7.4) relates the energy contained in all batteries of the contracted PEVs to
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the total battery capacity of the vehicles. Hence, it calculates the SOC of the aggregated PEV storage [37, 38, 152].

7.2 Modeling the RES Infeed Error using a Wind Forecast and a Turbine Model

Due to the fluctuating nature of RES, discrepancies between the planned RES generation output and the actually generated power arise during operation. In the following, wind power is considered as a RES. Other RES to be considered could be photovoltaic generators. The wind infeed error can be derived from a wind forecast time series and wind speed measurement series.

Wind forecasts are used for day ahead power production planning. The wind power generators need to announce their production one day in advance so that the residual demand can be covered by conventional generation sources, such as coal, nuclear or hydro [20, 100, 153]. The wind generators utilize meteorologic models to forecast the wind speeds and the tentative power production for the next day. The forecast used in the following is based on a meteorological model developed by the Consortium for Small-Scale Modeling (COSMO). The available forecast facilitates numerical weather prediction models and is abbreviated COSMO-2 [154]. It uses a geographical grid with a 2.2 km spacing and offers a 24-hour wind speed forecast. The small spacing of the geographical grid should allow an accurate forecast. It is updated every three hours in order to keep the error between the actual and the forecasted wind speed as small as possible. This follows the rationale of trying to use the latest weather measurements in order to predict the wind speed more accurately in the nearer future [155].

The produced wind power directly depends on the wind speed. Minimum wind speeds are needed for production. Between the minimum and maximum wind turbine output power, the power output of the generator depends nonlinearly on the speed and can be calculated by

\[ P_{\text{Wind}}(T) = \frac{1}{2} \rho_{\text{air}} C_p \pi r_{\text{rotor}}^2 v_{\text{Wind}}^3(T) , \quad (7.5) \]

where \( \rho_{\text{air}} \), \( C_p \), \( r_{\text{rotor}} \) and \( v_{\text{Wind}}(T) \) denote the air density, the capacity factor [156], the radius of the rotor blades and the wind speed,
7.2. Modeling the Wind Infeed Error

The equation is used to calculate the forecasted power generation and the actually produced power. In order to account for a worst case scenario, wind measurements and a forecast time series from a mountain-top site are utilized. Recently, in Switzerland, wind generators are built in the mountains due to an advantageous wind situation. However, the wind is gusty at the mountain tops and makes reliable forecasts difficult. The wind infeed error is calculated according to

$$\Delta P_{\text{Wind}}(T) = P_{\text{Wind}}^{\text{measured}}(T) - P_{\text{Wind}}^{\text{COSMO-2}}(T).$$

Figure 7.2 illustrates the forecast error of the COSMO-2 prediction model. One 1 GW wind park consisting of 200 wind turbines, with a rating of 5 MW each, is modeled through a single turbine model. The infeed error can be substantial. The maximum wind infeed error for this specific wind speed time series is 325 MW. Here, the update of the COSMO-2 forecast, which is indicated by the colored dots, does not deviate much from the original day ahead forecast. This is not necessarily the same for all time series’ available.
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Figure 7.2: Wind prediction infeed error of a 1 GW wind park. The park is modeled through (7.5) and the error is calculated through (7.6).

7.3 Brief Introduction to Model Predictive Control

Model Predictive Control (MPC) does not designate a specific control strategy. It targets a range of control methods which make use of a process model to determine a control signal maximizing an objective function. MPC approaches include the explicit use of a model to predict a process output in upcoming time instants. These future time instants are referred to as the optimization horizon. The goal is to calculate a sequence of control inputs to the system at hand starting from the actual time instant. The sequence of inputs should maximize the objective function for the predefined optimization horizon. The optimization is performed using a receding horizon strategy. This implies that at each instant the horizon is displaced one instant towards the future. From the sequence of calculated control inputs only the first one for the actual time step is applied to the system. The other control inputs, which represent future control inputs, are disregarded.

The general methodology of MPC is depicted in Fig. 7.3. The future outputs for a determined horizon $N^{RH}$, which is called prediction horizon,
are predicted at each time instant $t$ using the process model. The predicted output $y(T + i|T)$ for $i = 1...N^{RH}$ depends on the known values of the process up to instant $T$ and on the future control inputs $u(T + i)$ which are determined by the MPC problem solution. The set of future control inputs is calculated by optimizing a specific criterion which allows to keep the process as close as possible to a reference trajectory. The control effort can be included in the objective function. The control inputs $u(T)$ are sent to the process whilst the control inputs for future time instants are rejected because, at the next sampling time, $y(T + 1)$ is already known. Then, solving the MPC problem is repeated but with the updated system state and all the control input sequences brought up to date. Thus, $u(T + 1|T + 1)$ is calculated using the receding horizon with new information on the system state, including unanticipated disturbances.

The basic structure which allows to implement the MPC strategy is shown in Fig. 7.4. A system model is used to predict the future system state, based on past and current values of the inputs as well as on the proposed optimal future control inputs. The control inputs are calculated by the optimizer taking into account the cost function and the system constraints. The objective function considers the tracking error. The constraints incorporate limitations of the actuators available in the system. The process model must be able to capture the process dynamics to precisely predict the future outputs. Often, a state space model is utilized. The derivation of the controller for multivariable processes is simple [157, 158].
7.4 Model Predictive Control for Balancing RES with PEVs

Using MPC for scheduling V2G services offers the advantage of considering limitations on individual actuators while optimizing a system for a future which is unknown and which can be affected by unanticipated disturbances. When using PEVs for balancing a RES error, the system model is relatively simple to derive. The system mainly comprises the aggregated PEV battery storage. The reference trajectory for the MPC setup can be derived from the RES forecast and actual RES infeed. The disturbances to which the system is subject to include unanticipated behavior of PEVs, e.g., unplanned departures or arrivals, and deviations of the infeed from the anticipated error. In order to add flexibility to the system, a Combined Heat and Power (CHP) plant and a slack bus, which represent the bulk power system, are added.

The aggregated representation of vehicles in V2G mode and the flexible generators are then combined in one decoupled Multi-Input-Multi-Output (MIMO) dynamical system for the control problem formulation. In the following, the objective of the control problem is to balance the wind prediction infeed error by mainly using PEVs, contracted and aggregated for V2G purposes and, if necessary, a flexible CHP plant as well as a the slack bus. Thus, the latter are the available actuators [37].

The CHP plant incorporates a heat storage which is utilized to provide or consume heat when the previously determined power setpoint of the
CHP is changed. For the formulation of the control problem, it is useful to represent the dynamical system such that all input and state variables are equal to zero in steady state. Therefore, a coordinate translation can be performed for each actuator. The translation moves the origin to the scheduled value, which is the steady-state working point. Thereafter, the system is represented in $\Delta$-quantities describing deviations from the scheduled values:

\[
\begin{align*}
\Delta P &= P - P_{sch} , \\
\Delta E &= E - E_{sch} .
\end{align*}
\]

(7.7)

In the case of PEVs, it is assumed that the vehicles are in the *Idle* state when first connected to the power system and no control input signal is imposed. Thus, the scheduled steady state power setpoint is zero. The scheduled value of the aggregated storage’s SOC is chosen to 0.55 as this represents about the middle of the permissible energy range\(^1\). Thus:

\[
\begin{align*}
\Delta P_{V2G} &= P_{V2G} - 0 , \\
\Delta E_{V2G} &= E_{V2G} - 0.55 .
\end{align*}
\]

(7.8)

For the CHP plant, it is assumed that it is operated in the middle of its operational capacity band, so the the ramping capabilities are symmetrical. Its heat storage is assumed to be filled to 50% of its capacity, hence:

\[
\begin{align*}
\Delta P_{CHP} &= P_{CHP} - \left( P_{\text{min}} + \frac{P_{\text{max}} - P_{\text{min}}}{2} \right) , \\
\Delta E_{CHP} &= E_{CHP} - 0.5 .
\end{align*}
\]

(7.9)

The slack bus does not incorporate a maximum or minimum energy bound nor a power limit. Therefore, the shift to $\Delta$-quantities is straightforward and not stated here.

Finally, the system’s equation can be formulated in discrete standard notation as

\[
\begin{align*}
x(T + 1) &= A_d(T)x(T) + B_d(T)u(T) , \\
y(T) &= x(T) .
\end{align*}
\]

(7.10)

where the initial condition is $x_0 = x(T = T_0)$ and the state and input variables are defined as

\[
\begin{align*}
x(T) &= [\Delta E_{V2G}^{rel}(T) \Delta E_{CHP}^{rel}(T) \Delta E_{slack}^{rel}(T)]^T , \\
u(T) &= [\Delta P_{V2G} \Delta P_{CHP} \Delta P_{slack}]^T .
\end{align*}
\]

(7.11) (7.12)

\(^1\)It is assumed that 0.3 p.u. is the lower bound and 0.8 p.u. is the upper bound for the individual PEV battery energy range. Hence, if all PEVs in V2G mode are fully depleted, the lower energy bound of the aggregated storage is 0.3 p.u. as well.
The system matrices are found to be diagonal because of the decoupled nature of the system actuator dynamics. A detailed example on how the matrices can be derived is found in Appendix K for the more complex case of the CHP heat storage\(^2\). For expressing the matrices in compact notation, the "diag" operator is used on a column vector which describes the main diagonal:

\[
\begin{align*}
A_d(T) &= \text{diag} \left[ \begin{array}{c}
\frac{1}{\tau_{\text{CHP}}} \\
0
\end{array} \right], \\
B_d(T) &= \text{diag} \left[ -\tau_{\text{CHP}} \frac{E_{\text{max}}^- \left( \frac{1}{\tau_{\text{CHP}}} t \right) - 1}{E_{\text{max}}^{\text{CHP}}} \\
0
\end{array} \right].
\end{align*}
\]

The MPC problem is formulated to minimize

\[
J(s) = \sum_{s=0}^{N_{\text{RH}}-1} u^T(T+s|T)Ru(T+s|T) + \sum_{s=0}^{N_{\text{RH}}-1} x^T(T+s|T)Qx(T+s|T)
\]

subject to

\[
x(T+s+1|T) = A_d(T+s|T)x(T+s|T) + B_d(T+s|T)u(T+s|T)
\]

\[
\Delta P_{\text{Wind}}(T+s) = u_1(T+s|T) - u_2(T+s|T) - u_3(T+s|T)
\]

\[
\Delta P_{\text{V2G}}^{\text{min}}(T+s|T) \leq u_1(T+s|T) \leq \Delta P_{\text{V2G}}^{\text{max}}(T+s|T)
\]

\[
\Delta P_{\text{CHP}}^{\text{min}}(T+s|T) \leq u_2(T+s|T) \leq \Delta P_{\text{CHP}}^{\text{max}}(T+s|T)
\]

\[
\Delta P_{\text{slack}}^{\text{min}}(T+s|T) \leq u_3(T+s|T) \leq \Delta P_{\text{slack}}^{\text{max}}(T+s|T)
\]

\[
\Delta E_{\text{rel}}^{\text{min}}(T+s|T) \leq x_1(T+s|T) \leq \Delta E_{\text{rel}}^{\text{max}}
\]

\[
\Delta E_{\text{V2G}}^{\text{rel}} \leq x_2(T+s|T) \leq \Delta E_{\text{V2G}}^{\text{rel}}
\]

\[
\Delta E_{\text{CHP}}^{\text{rel}} \leq x_3(T+s|T) \leq \Delta E_{\text{CHP}}^{\text{rel}}
\]

\[\Delta E_{\text{slack}}^{\text{rel}} \leq x_3(T+s|T) \leq \Delta E_{\text{slack}}^{\text{rel}}\]

\(^2\)In contrary to the electric vehicles, the heat storage incorporates losses due to convection of heat through the walls of the storage device. In case of the PEV battery, no energy losses over time are assumed.
and

\[
R = \text{diag} \begin{bmatrix}
\gamma_{r,v2G} \\
\gamma_{r,\text{CHP}} \\
\gamma_{r,\text{slack}}
\end{bmatrix}
\]

\[
Q = \text{diag} \begin{bmatrix}
\gamma_{q,v2G} \\
\gamma_{q,\text{CHP}} \\
\gamma_{q,\text{slack}}
\end{bmatrix}
\]  \hspace{1cm} (7.17)

Some degrees of freedom exist in the construction of the cost function for the MPC strategy. The main task of the controller is to decide which actuator shall be used in order to cause the least possible impact on the controlled system while balancing the error \(\Delta P_{\text{Wind}}(T)\). The objective function, given in (7.14), can be designed to incorporate this rationale. The first summand penalizes the absolute deviation of an input from its steady-state value. This avoids that actuators are excessively utilized when there is no need. The second summand penalizes the deviation of a state from its steady-state value. This is suitable for actuators whose SOC should be kept around the desired level.

The penalization factors used in the objective function are given in (7.17). They can be freely chosen and are subject to preferences on the actuator utilization. In general, the penalization factors are tuning parameters and need to be determined by trial and error to achieve a proper behavior of the MPC controller. A routine to determine proper parameters is not developed herein.

The control objective is subject to constraints given in (7.15a)–(7.16g). The system state equation, given in (7.15a), is used as an equality constraint. It gives that the state of the next time step is dependent on the actual state and the input \(u(T+s|T)\) in time interval \(T+s\) of the receding optimization horizon. The equality constraint (7.15b) ensures that the RES infeed error \(\Delta P_{\text{Wind}}(T)\) is always fully balanced by the actuators in the system. PEV load, which is used for balancing, is counted positive while the generators’ contributions, including the slack bus, are counted negative. Thus, lowering the setpoint of a generator contributes to the balancing of an unplanned oversupply of wind energy. This in accordance with the wind error definition given in (7.6).

The constraints (7.16a)–(7.16c) limit the range of the input variables to the possible power ratings of the controlled devices. The maximum and minimum power output values incorporate a temporal dependence. This is due to the SOC of the generator storages as well as the temporal and
spatial variability of the PEVs. The constraints (7.16d)-(7.16f) limit the state variables, i.e., the SOC of the different storages in the system in order to avoid overloading or depletion of the storages.

7.5 Using Heuristics to Schedule Individual PEVs for V2G services

The control inputs, determined by the central MPC, are used to alter the setpoints of the system actuators. Many studies, such as [25, 103, 159], stop at this point. However, taking advantage of the detailed information from the transportation simulation, described in Chapter 6, and the accurate electricity network model, impacts of V2G services on the network can be studied in detail. Individual vehicles, which are distributed throughout the network, can be scheduled to provide V2G service according to the calculated actuator setpoint. The service changes asset utilization degrees as well as the power flow in the network.

When deciding which individual vehicle in the fleet should provide V2G services, a scheduling rule needs to be derived. One possibility would be to determine the power setpoint of a PEV by an individual factor proportional to the power rating available from the specific vehicle. However, this could introduce problems for the distribution network as many PEVs could be activated at the same time and in the same area supplied by one transformer. This could potentially stress the transformer, i.e., lead to an overload. Another solution is to use the concept of priority lists [160], which are based on heuristics.

Heuristics and meta-heuristics are applied for various problems in power systems [161]. Heuristics have the advantage to be fast. However, they do not necessarily find the global optimum. Meta-heuristics have proven to deliver good results in unit commitment problems [162] and have been utilized for PEV scheduling [62]. Heuristic schemes can be useful for the PEV aggregator when having to decide quickly how to schedule the vehicles optimally or at least with acceptable performance.

The priority lists include PEVs contracted for V2G services. The lists include information on the maximum available nodal capacity for providing V2G, i.e., feeding or drawing power at a particular node. The priority lists can be created by a heuristic formulated as
7.6 V2G Wind Balancing Case Study

\[ u_{V2G}(T) = \Delta P_{V2G}(T) = \begin{cases} 
0; & \text{sort ascending } \left\{ \frac{e_{V2G,v,n}(T)}{C_{v,n}} \cdot T_{dep}^{v,n} \right\} \\
< 0; & \text{sort descending } \left\{ \frac{e_{V2G,v,n}(T)}{C_{n,v}} \right\} 
\end{cases} \]

\[ \forall v \in \mathcal{V}_n(T) \wedge \forall n \in \mathcal{N} \quad \text{(7.18)} \]

where \( \frac{e_{V2G,v,n}(T)}{C_{v,n}} \) and \( T_{dep}^{v,n} \) denote the SOC of the particular vehicle and its anticipated departure time step, respectively. The variable \( u_{V2G}(T) \) denotes the control input for the aggregated PEV storage. The variable is calculated solving the MPC problem.

The heuristic takes into account the departure time of the individual PEVs. In case of a positive control signal, the wind infeed error will, according to (7.6), be positive and the car with the lowest value of the product will be recharged first. In case the wind error is negative and the cars need to discharge, the PEV with the highest SOC is scheduled first.

The priority lists include information on the network state. The lists limit the scheduling of vehicles which are parked in areas congested by uncontrolled or controlled charging. Therefore, the vehicles which are parked in these areas cannot be scheduled for charging but only for discharging. However, other heuristics or even optimizations could be envisioned for this purpose [100].

7.6 Case Study: Balancing Wind Infeed Error using a PEV Fleet and V2G

The aggregation scheme described before is used in the following case study for wind power balancing. As now the third possible PEV operation mode is finally introduced, this case study takes advantage of the operational state description developed in Chapter 3. Here, PEVs can connect to the power system in all of the previously defined operational states, previously defined in Fig 3.1. The aggregator controls the vehicles and induces transfers between the modes when necessary. The transfers are utilized to ensure that each vehicle obtains its desired SOC at departure. The figure is repeated here for convenience reasons.

When a vehicle, which is contracted for V2G services, connects to the network, it is assumed to be in the Idle state until it is scheduled by the
central MPC controller and the underlying heuristic to supply V2G services. The actual action which the vehicle then undertakes, i.e., charging or discharging, is dependent on the signal determined by the MPC controller of the PEV aggregator. To this end, vehicles which are chosen by the heuristics perform a state transition from the *Idle* state into either the *Feeding Power* or the *Drawing Power* state.

Other vehicles, which are not contracted for V2G services connect in the controlled charging mode. The control approach used in this mode is discussed in Chapter 5 and demonstrated in Chapter 6.

Uncontrolled charging is also integrated in this case study. In this mode, the vehicles charge at the maximum power limited by the physical connection capacity. In case too many PEVs are in this mode and would overload the particular transformer, the available transformer capacity is divided between the PEVs according to their connection capacity share of the total demand.

As vehicles in V2G mode can be in the *Idle* state or the *Feeding Power* state for a substantial amount of their parking duration, they might not be able to attain their desired SOC at departure. The aggregator is able to detect this and induce a transfer for such vehicles from the V2G mode.
into the controlled charging mode. This mode transfer is performed three time steps ahead of the time where no charging flexibility is left. These vehicles feature a high value of the agent type parameter in the controlled charging mode and are preferred to be scheduled for charging. However, if the particular transformer is heavily congested, the vehicles could not be fully scheduled for charging. In such a case, the rest of their charging flexibility is used up.

In case no charging flexibility is left, the vehicles transfer from the controlled charging mode into the uncontrolled charging mode. This is performed one time step ahead of the situation where no charging flexibility is left. This transfer moment is chosen in order to ensure that even in the case the transformer is congested by PEVs in uncontrolled charging mode, the risk is low to not obtain the desired SOC at departure. Note that a transfer path can start from the V2G mode and go over the controlled charging mode into the uncontrolled charging mode.

For the V2G case study a high penetration PEVs is assumed. Therefore, the mobility scenario modeled in the year 2050 of Scenario C is chosen. Initially, 10 % of the vehicles apparent in this scenario are assumed to be contracted by the aggregator for V2G services and 90 % of the PEV fleet are operated in the controlled charging mode.

The complete system controlled herein consists of the wind power balancing signal, PEVs, a CHP plant and a slack bus. The aggregator uses an receding horizon which allows to look three time steps ahead of the current time step. For these time steps, the aggregator calculates the energy storage of the aggregated PEV battery and the controllable power for charging and discharging this battery. As the aggregator also controls a CHP, it tracks the state of its CHP heat storage as well. The CHP is operated at 120 MW power output. It is assumed that the CHP can ramp up to 200 MW and ramp down to 40 MW almost instantaneously in one time step, leaving a total flexibility of ± 80 MW per time step. The MPC controller is also able to draw power from or feed power into large power system which is modeled by a slack. The slack does not include a storage.

The penalty factors, given in Section 7.4 in (7.17), are chosen such that the aggregated PEV storage is selected whenever possible to supply the balancing demand. The penalty factors for the PEV control input and the PEV state variable are chosen to be zero. The CHP plant actuator is penalized with slightly higher values than the PEV actuator. The CHP
Figure 7.6: Illustration of V2G wind balancing service. Actuator setpoints are calculated by the MPC scheme.
(a) Wind prediction infeed error and contributions of the different actuators when balancing the error.
(b) Actuator setpoints calculated by the MPC scheme.
(c) Relative energy level of the different storages in the controlled actuator portfolio.

Penalization value is chosen such that the difference of using PEVs or the CHP plant remains rather small. The by far highest penalty factor is selected for the utilization of the slack bus as impacts of the wind error on the bulk power system should be avoided whenever possible. The aggregator balances a wind prediction power infeed error of a 400 MW wind park which is modeled according to Chapter 7.2. As the update of the wind production prediction does not offer much more information, i.e., the error is not much reduced, it is assumed that the aggregator is able to utilize a much more accurate prediction for the upcoming three time steps. In specific, it is assumed that the wind prediction infeed error is known for these time steps.

Figure 7.6 gives a compact illustration of how the aggregator uses its actuators to balance the wind error. The effects are shown on an aggregated level. Figure 7.6(a) displays the infeed error to be balanced through the dashed, black line. The error is negatively biased during the
day but exhibits some positive outliers. The contribution of the PEVs, the CHP and the slack is shown in green, red and grey, respectively.

The PEVs supply most of the desired balancing service. The negative bias poses a disadvantage for the PEVs as they need to constantly discharge and feed energy into the network. Particularly during times when the error is very large, e.g., at 07:45, at 15:30 and at 23:15, the CHP is activated and contributes largely to the desired total balancing service. At 23:15, some power is contributed by the slack for the balancing service. The preference for PEVs is, as mentioned before, enforced by the penalization parameters in the objective function of the MPC algorithm.

The control inputs, calculated by the central controller, are illustrated in Fig 7.6(b). The state variables are shown in Fig. 7.6(c). The state variables are plotted in relative terms, i.e., as deviations from their steady state values. For the CHP the steady state value is chosen to 50% of the storage content. For the PEVs it is chosen to be 60% of the total available storage. Note that the total storage varies strongly for the aggregated PEV storage but stays rather constant for the CHP heat storage. This is explained a bit later.

Figure 7.6(b) underlines one advantage of using MPC. The receding horizon optimization is able to anticipate upcoming outliers of the error and to react accordingly. During times when the PEV cluster is not able to solely balance the infeed error, e.g., at 07:45 or particularly at 23:15, the controller chooses to use the CHP or, if necessary, the slack.

At 07:45 in the morning a large overproduction of the wind park is apparent. The CHP contributes to balance this overproduction by revising its production setpoint downwards. In order to avoid a high penalty, the CHP setpoint is revised upwards before the actual overproduction occurs. Hence, the CHP state variable, i.e., the content of the CHP heat storage, is increased before. This minimizes the overall deviation from the steady state value. Afterwards, the setpoint of the CHP is revised upwards again to compensate for the rest of the state variable deviation from its steady state. This oscillation can be noticed at all times when the CHP needs to be utilized for balancing services. The shape of this oscillation is dependent on the choice of the CHP penalization factors. Note that a downward revision only would lead to a high deviation of the CHP heat storage content from its steady state. The deviation would last rather long as the dynamics of heat convection are slow; see Appendix K. Then, the penalty faced by the controller would be high.
Figure 7.7: Aggregated V2G service potential of the aggregator.

(a) Available control power of the aggregated PEV storage in both directions.
(b) PEV battery cluster content.
(c) PEV number in V2G mode.

Figure 7.6(c) shows the evolution of the aggregated PEV storage state variable. It is illustrated in green. The evolution is affected by several effects such as the balancing service provided by the PEVs, the arrival of PEVs connecting in V2G mode, the transfer of PEVs from V2G mode into the controlled charging or the uncontrolled charging mode and, finally, the departure of PEVs. The impact of the V2G service is easily noticed at times when the error, and therefore the demanded service from the PEVs, is large. During these times, a steep increase of the PEV state variable is found, e.g., at 04:30, at 07:45, at 15:30 and at 23:15.

The overall trend of the PEV state variable is, however, dominated by the arrival, departure and the mode transfer behavior of the PEVs. The decrease of the state variable from a value of 0.13 p.u. at 00:00 to a value of -0.19 p.u. at 06:00 is, on the one hand, due to the continuous discharging of the battery for balancing services but is, on the other hand, also caused by the departure of PEVs. The continuous increase thereafter obviously cannot be due to balancing service provision only.
because the signal is negatively biased. In fact, a large number of PEVs connects during these hours as described before in the scenario analysis, which is found in Section 6.5. The arriving PEVs feature a high SOC and hence increase the overall, average SOC of the virtual battery.

Figure 7.7 shows the V2G service potential available to the aggregator throughout the day. It includes the effects of providing balancing service. Figure 7.7(a) shows the aggregated power of the battery for positive service, i.e., charging, and for negative service, i.e., discharging. The overall available, controllable power is large. The band of the available power fluctuates between about +25 MW and -50 MW at minimum and about +75 MW and -145 MW at maximum. Figure 7.7(b) shows the energy content in the aggregated battery. It is directly related to the total number of PEVs active in V2G mode. The latter is depicted in Fig. 7.7(c).

A maximum of around 17’000 PEVs is active at 14:00 in V2G mode. This number decreases to about 8’000 PEVs at around 06:00. The battery energy content of the PEV cluster, i.e., the aggregated, virtual storage, incorporates the same evolution. It fluctuates between 0.25 GWh and 0.5 GWh with the same temporal location of the maximum and minimum. Note that the energy is distributed in a heterogenous manner between the individual PEVs and is dependent on the fleet composition and the simulated transportation behavior. The evolution of the battery energy content confirms the reasoning on the evolution of the PEV state variable. In fact, looking more closely into Fig. 7.7(b) and Fig 7.7(c) while comparing it with Fig. 7.6(c), it can be noticed that the steep increase of the PEV state variable at 04:30 is mostly due to the balancing service. At this time few PEVs are available in V2G mode. The rather small number of PEVs has to compensate an overproduction which highly effects the SOC of the individual PEVs and hence the aggregated storage.

Comparing Fig. 7.7(a) with Fig. 7.6(a) it can be noticed that the CHP is utilized during times when the wind power infeed prediction error is larger than the available controllable power of the virtual PEV storage. Noticeable are the incidents at 04:30, 07:45, 15:30 and at 23:15. The situation at 23:15 shows a case when the wind infeed prediction error is very large but the controllable PEV power is small.

Obviously, substantial balancing services have an impact on the load curve of the urban area in which the PEVs performing the V2G ser-
Figure 7.8: Zurich's aggregated load curve and the effect of V2G service provision.

vices are located. Here, it is assumed that all PEVs are located in the metropolitan area of Zurich. The effect of the V2G service on the metropolitan area load curve is shown in Fig. 7.8. The figure depicts three different load curves. The black, dashed curve shows the city base load in the year 2010 without PEVs.

The blue curve shows the city's load curve for Scenario C, the year 2050 and controlled charging. Be reminded that only 90% of the PEVs from this scenario are initially participating in the controlled charging scheme described in Chapter 5 and Chapter 6. However, the shape of this curve is somewhat altered compared with the one shown in Fig. 6.34 found in Chapter 6.5. This is because the curve shown in Fig. 7.8 includes transfers from the V2G into the controlled charging mode. The transfers exhibit a different temporal behavior than when simulating controlled charging only. The mode transfers are heavily affected by the V2G provision. In the case studied here the error is negatively biased and therefore the transfers are enabled earlier as would have been the case for a positively biased error. The vehicles in the uncontrolled mode heavily load the underlying infrastructure of the city. The red load curve illustrates the effect of V2G service provision. The provision is superimposed on the base load and on the controlled PEV load.
Obviously, the provision of V2G services strongly affects the final load curve of the city. Controlled charging barely changes the shape of the load curve. It increases the overall load on the electricity infrastructure\(^3\). In general, the total load of the city including the V2G service is reduced as the balancing service is negatively biased. During low load hours, the load in the V2G case falls below the minimum load seen in the base case. However, at times when the wind park produces too much power, large load spikes can be seen in the curve. Note that neither the controlled charging nor these load spikes endanger the underlying electricity infrastructure due to the control algorithm.

Figure 7.9 zooms into the load situation of the city’s network. It shows the PEV load at each node of the electricity distribution system of the city of Zurich throughout the day. Figure 7.9(a) depicts the load of the PEV fleet operated in the controlled charging mode. Note that it now includes the load of vehicles which transferred from V2G into the controlled charging mode. They need to consume more energy as they provided for balancing the wind error.

The PEV load distribution is similar compared to Fig. 6.32(c) in Chapter 6. The load shape of many nodes is likewise. Noticeably, the number and the size of load peaks is increased. An increased number and size of load plateaus is also observed. Many load plateaus are extended in their temporal appearance. The temporally extended load plateaus and additional load peaks are indicated in the figure. The different shape of the PEV load is due to the V2G provision. More energy is demanded by PEVs in the uncontrolled and controlled mode as some of them had to feed energy into the grid for wind balancing purposes. This energy needs to be reacquired. As more PEVs with an increased demand for energy charge in the network, the load peaks become larger and the degree of node congestion increases. The latter is indicated by the duration of the load plateaus.

Figure 7.9(b) also illustrates the PEV load at each node but now includes the impact of V2G service provision. The load looks more spiky at almost every node in the electricity system. The size of the load peaks is reduced compared to the controlled charging case. The formerly observed load plateaus, indicating congestions, can still be noticed but are not as evident as before. This is due to the power feedback of PEVs.

\(^3\)The smart charging algorithm is active and therefore the infrastructure and its secure operation is not endangered.
Chapter 7. Provision of V2G Services

(a) PEV load without V2G contribution at every node in the electricity distribution system throughout the day.

(b) PEV load with V2G contribution at every node in the electricity distribution system throughout the day.

Figure 7.9: Effect of V2G service provision on the PEV load distribution at every node of the electricity distribution system of the city of Zurich throughout the day, Scenario C, year 2050.
It reliefs congestions at some nodes and hence alters the load plateau shape. Additionally, PEV load now becomes negative. Values down to -0.7 MW are observable in the figure. They indicate power which is fed by PEVs into the network. However, the nodes at which this appears do not become generation nodes. They remain load nodes. The formulation given in (7.1)–(7.3) prohibits that the PEV power infeed becomes larger than the load at these nodes.

Figure 7.10 shows the V2G service contribution provided by the PEVs at the different nodes in the electricity distribution system throughout the day. Figure 7.10(a) mainly shows the positive contribution, i.e., charging, while Fig. 7.10(b) shows the negative contribution, i.e., discharging. Note the different color code for these figures.

In Fig. 7.10(a) it can be seen that for most of the time no positive service is provided. Large parts of the area remain green, i.e., no load is imposed by PEVs in V2G mode. During times when overproduction occurs, load peaks up to 1 MW are observed. This is not particularly much in the light of a maximum balancing demand of up to +150 MW. The reason is that the service provision is effectively distributed by the heuristic between the different nodes. Note that for the provision of positive service, the physically limited node potential is considered. although 1 MW of PEV load can be much for transformer in place, the algorithm ensures that no overloads occur. For any provided V2G load peak, the maximum node capacity, i.e., the transformer capacity, is not violated.

Figure 7.10(b) visualizes mainly the power infeed from the PEVs. Several effects can be seen. First, the area is mainly colored in magenta which shows that PEV power is fed in at many nodes throughout the day. The desired power infeed due to the wind error is small. Thus, the power fed in at the distribution system nodes is also small. PEVs are discharged which incorporate a very high SOC. These vehicles are distributed over the whole system and hence the infeed error is distributed between many nodes.

When a large infeed is required, the PEV infeed concentrates mainly on few nodes. Their infeed is found to be in the range of -0.6 MW down to -1 MW. These nodes typically feature a large number PEVs. Thus, the number of vehicles with a high SOC is also large at these node. Additionally, the nodes exhibit a relatively high base load which allows the vehicles to feed a rather large amount of power into the system.
Chapter 7. Provision of V2G Services

(a) V2G service provision at every node in the electricity distribution system throughout the day; positive contribution.

(b) V2G service provision at every node in the electricity distribution system throughout the day; negative contribution.

Figure 7.10: V2G service provision at every node of the electricity distribution system of the city of Zurich throughout the day; Scenario C, year 2050.
Figure 7.11 further zooms into the system and illustrates the situation at three different nodes throughout the day. The figures show the V2G service potential available from PEVs connected at the nodes through the area plots. The V2G potential, determined by the load situation at the particular node, is illustrated by the red lines. They show the negative potential, i.e., for discharging, in the negative part of the abscissa and the positive potential, i.e., for charging, in the positive part. The actually provided V2G service at the node is shown through the green line.

Figure 7.11(a) shows the V2G service potential available from PEVs at node Nr. 333 through the area plot. The light blue indicates the positive potential and the dark blue area the negative potential as it evolves over time. The red lines indicate the V2G potential limits as they are imposed by the physical capacity of the node. They are not depicted as they are much larger than the V2G potential of the connected PEVs and thus the nodal capacity does not impose an active constraint here.

It is observed that the provided service always stays within the area plot, i.e., the service provided at this node finds its limit in the available PEV potential. After 45 minutes of providing negative control, i.e., feeding energy back to the grid, the connected PEVs are depleted at 09:30. Thereafter, the PEVs cannot offer negative service, which is why there is no potential indicated. At 10:00 there is demand for positive service. Some PEVs are scheduled for the service according to the heuristic. Remember, the heuristic chooses PEVs which have a low SOC and a short time to departure. As some PEVs are charged at 10:00, negative V2G potential is available again at 10:15. Noticeable is also the situation at 14:30. Then, no V2G potential is available at the node as all PEVs left. However, in the next time step, i.e., 15 minutes later, other PEVs arrive and V2G potential is again available.

Figure 7.11(b) shows the same information but for node Nr. 19. There, V2G potential from PEVs is available throughout the whole day. The potential from the connected PEV fleet is about as high as the one at node Nr. 333 but is never fully depleted at this node. The provision of the service does affect the shape of the PEV potential as well. It causes the band to be unsymmetrical. Note that the actually provided service at this node also stays within the band indicating the available, controllable PEV power. Additionally, the potential determined by the nodal capacity is plotted through the red line.
Chapter 7. Provision of V2G Services

(a) V2G service potential and actual service provision at node 333 of the electricity distribution system.

(b) V2G service potential and actual service provision at node 19 of the electricity distribution system.

(c) V2G service potential and actual service provision at node 298 of the electricity distribution system.

Figure 7.11: V2G service potential and actual service provision at different nodes of the electricity distribution system of the city of Zurich, Scenario C, year 2050.
7.7. Concluding Remarks

It is observed that after 07:00 the PEV potential is higher than the nodal capacity. Then, the provided V2G service is limited through the red line, i.e., the nodal V2G capacity. Note that at 08:30 and at 15:30 the nodal capacity is zero and no positive V2G service can be provided.

Finally, Fig. 7.11(c) shows a node where the available PEV potential for V2G is very large throughout the day. It is about 5–10 times larger as the potential at the other nodes shown. The potential is largest during the working hours, i.e., between 08:00 and 19:00. This is due to the scenario and the simulated agent behavior as many agents park at their work locations which feature charging options. Unfortunately, at this node, no positive nodal V2G service is available through extended periods of the day. This is due to many PEVs being connected in controlled and uncontrolled charging mode congesting this node. Solely a negative service is provided at this location throughout the day time. Notice the provision of positive service at 23:15. Then, positive capacity is available again and is desperately required since a large RES overproduction occurs.

7.7 Concluding Remarks

This chapter investigates the effects of V2G service provision on the distribution network of Zurich, Switzerland. To this end, it first describes an aggregation procedure for vehicles which are contracted for these services by an entity. The latter is assumed to be the aggregator. The clustering procedure pays full attention to the distribution network state. The state is determined by the inflexible base load, by PEVs in uncontrolled charging mode and by PEVs in controlled charging mode. The aggregator used the operational state description described in Chapter 3 and induces mode transfers in order to ensure that each vehicle receives the desired energy. The vehicles thus leave with the desired battery energy level.

The vehicles are used here to balance a wind forecast infeed error from a large wind power plant. To this end, the aggregator utilizes a MPC scheme to control the virtual PEV battery and other, auxiliary actuators. The actuators also include a CHP plant and slack, which models the bulk power system, i.e., ancillary services procured by the TSO. The aggregator prefers to schedule PEVs for balancing services and makes
only use of the other actuators if not enough capacity is available from the virtual PEV storage.

A case study is performed showing the feasibility of V2G services in the distribution network. Outstandingly, the case study herein offers the possibility to actually schedule individual vehicles to perform the desired actions, i.e. charging and discharging, in the network. To this end, heuristics, similar to priority lists, is used. This offers a high level of detail when investigating the networks effects of V2G, so far not reported in literature. The case study shows that by using only 10 % of a large PEV fleet, a negatively biased error is successfully balanced while the heavily loaded distribution network is not endangered through overloads or excessively low voltages.

This chapter finalizes the analysis tool for large scale electric mobility. The tool incorporates the three main modes, uncontrolled and controlled charging as well as V2G services while using realistic models on vehicle energy consumption and temporal and spatial connectivity behavior as a fundament for the analysis of PEV impacts on power systems.
Chapter 8

Conclusions and Outlook

This chapter concludes the thesis by summarizing the work, drawing conclusions and providing an outlook on potential, associated research.

8.1 Summary of the Thesis

The thesis develops an agent-based tool for impact analysis and demand management of large scale electric mobility in power systems and proposes a framework for application in planning and operation power systems. To this end, the thesis briefly revises the structure and the current legal as well as operational frameworks of power systems. Then, in order to provide a holistic approach for the management of electric vehicles, a planning and operation framework is developed which integrates three operation modes for electric vehicles in power systems. The operation framework is put in reference to an entity called PEV aggregator, which is envisioned to control the electric vehicles. The thesis elaborates how such an entity, following different business and operation objectives, can be integrated into current power system operation frameworks.

Moreover, a multi energy carrier approach is utilized to model the energy consumption of an individual PEV. The model is extended from a single step optimization to a multi period optimization. The multi period setup provides results on energy consumption which can be used to
generate worst case electric energy consumption regression models for individual vehicles. The energy consumption models are used as input for the simulation of PEV charging behavior. An agent-based demand management approach is further developed in order to mitigate challenges introduced by PEV charging. The demand management approach avoids stressing the underlying electricity infrastructure. The approach is shown to be able to provide valley filling as well as peak shaving services by controlling the charging behavior of large numbers of individual vehicles. The demand management approach is distributed, predictive and hierarchical.

Individual vehicle energy consumption regression models and the demand management approach are integrated with an multi agent transportation simulation tool (MATSim). This integration allows for detailed analysis of temporal and spatial charging behavior as well as of the PEV charging flexibility. Case studies are performed for the city of Zurich, Switzerland, showing the analysis and control capabilities of the integrated tool. Finally, the developed tool is used to simulate V2G services, balancing a large infeed prediction error from renewable energy sources while considering the underlying limitations of the electric infrastructure.

8.2 Conclusions

The results of this thesis and its herein developed tools reveal several aspects concerning the large scale integration of electric vehicles in the power system. From a conceptual perspective, it appears to be favorable and possible to integrate recently discussed aggregator concepts into the current power system structure. As the operation paradigm of power systems is likely to change and distribution networks will become more active, current planning and operation frameworks need to be adapted in order to allow for the envisioned services. Furthermore, it is shown that planning of V2G services has to be considered together with the charging schedule of vehicles which are not contracted for V2G services. Otherwise, the aggregator could introduce a large consumption forecast error which would need to be balanced using costly, conventional ancillary services. Also, this could endanger distribution system assets and cause additional congestions.
From a modeling perspective it is shown that the multi energy carrier modeling approach can effectively be used to model PEVs of different architecture. The simulation results indicate that, depending on the optimization technique, the electricity consumption can greatly vary. However, the vehicle model can efficiently be integrated into the electric mobility analysis tool.

The results of the developed analysis tool show that large scale adoption of electric mobility could endanger the operation of the current infrastructure. Local overloads are detected and low voltages are likely to occur for other PEV scenarios. Two solutions can be envisioned to these challenges. First, a costly expansion of the network could be performed in order to accommodate the electricity demand of a growing electric fleet. Secondly, and consistent with the smart grid movement, intelligent control approaches such as the one proposed herein, could be utilized to avoid endangering system security and operation. Bidirectional ICT penetration in power, and especially distribution, systems is crucial to this end. Then, as the simulations show, even large numbers of electric vehicles can be supplied in a secure manner.

Additionally, the results suggest that V2G services, such as balancing RES or providing ancillary services, are possible with proper control approaches. These control approaches have to take the underlying constraints of the physical infrastructure into account. Otherwise, V2G services, anticipated to be advantageous for the power system, could easily stress the operation of the network and its individual assets. Here as well, careful consideration has to be paid to the ICT solutions which need to be introduced to allow for the services. In any case, the ICT solution should allow both, the planning of these services as well as the actual control of the individual vehicles with an application case dependent temporal and spatial resolution.

8.3 Outlook

For further research on the topic of electric vehicle integration and the related charging management various topics are conceivable. The conceptual framework for the integration of an aggregator into power system operation could be further improved. The proposed framework is realistic but lacks an economic as well as a detailed technical evaluation. The latter would be particularly interesting in terms of needed
communication technologies. Also, upcoming regulatory concepts, such as incentive regulation schemes, should be considered in the framework. To this end, the design of appropriate rules, rights and responsibilities is crucial. Furthermore, the design of appropriate compensation schemes between aggregators, suppliers and network operators is clearly another topic of interest.

The demand management scheme could also be further improved in order to incorporate more functionalities. It remains to be investigated how the demand management approach, which actually considered exogenous price signals, can be extended to implement price dependent charging. Then, the profit of an aggregator could be quantified. Additionally, the demand management concept could be extended to manage line overloads if they solely occur. So far, this is not fully implemented.

The integrated analysis tool with information feedback to MATSim offers the possibility to investigate how transportation behavior is altered by charging constraints of the electricity infrastructure. A case study has been performed on a small scale system, i.e., four node, test system. It remains to be shown that the smart scheduling approach is also feasible for large scale system as the one studied with the non-iterative scheme.

One could envision a coordination scheme of the proposed charging algorithm, which is focussed on distribution networks, with an intelligent charging algorithm on the transmission level. This higher level charging algorithm could then take costs of power generation and constraints on such into account. As the proposed demand management scheme takes exogenous price levels as input for the PEV scheduling, it is possible to integrate it with locational marginal pricing schemes.

The current way of V2G service provision could be augmented in different ways. Future work could improve the heuristics which is used to schedule individual vehicles contributing to V2G services. Also, the consideration of the underlying infrastructure could be enhanced in terms of allowing an infeed of energy, i.e., a bidirectional power flow. So far, the load at the individual network nodes limits the power infeed from the vehicle. The MPC V2G approach could be extended to provide ancillary services for a TSO such as secondary or tertiary reserves. Detailed case studies would reveal the feasibility of using PEVs for such purposes.

Moreover, a proper planning approach for determining available reserves for V2G services still has to be developed.
Im Herzen eines Menschen ruht der Anfang und das Ende aller Dinge.

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## Appendix A

### PEV Energy Hub Parameter Table

<table>
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<tr>
<th>PEV energy hub data</th>
<th>Unit</th>
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Table A.1: Parameters used to simulate the PEV energy hub model in the single and the multi period version.
Appendix B

Proof of Incentive Rationality and Incentive Compatability for the Revelation Theorem

A strategic form game is usually played iteratively. The agents learn a strategic behavior during the rounds when the game is played. For demand management of large PEV populations and big electricity networks such an iterative approach appears to be computationally expensive and thus a painstaking solution. The iterative process would need to be performed at every node in the network.

Finding a dominant strategy could circumvent this issue. A dominant strategy is a strategy which the agents always choose in the ongoing game due to the rules of the game [121,163]. One dominant strategy could be to reveal the true agent type or, as termed here, their personal valuation parameter. In game theory, this behavior is induced by the so called revelation theorem. The revelation theorem states that if two mathematical problems, the incentive rationality and the incentive compatibility theorem, can be proven, the agents will always reveal their true personal parameters [121,163].

Thus, in order to circumvent an iterative demand management scheme, first the incentive rationality constraint needs to be proven.
Appendix B. Incentive Rationality and Compatability

B.1 Proof of Incentive Rationality for Utilizing the Revelation Theorem

The incentive rationality constraint is formulated in a generalized way as

\[ u_{v,n}(T, \Omega_{v,n}(T), \pi_n(T), \theta_{v,n}(T)) \geq 0, \quad (B.1) \]

with the substitution

\[ \Omega_{v,n}(T) = soc_{v,n}(T) - soc_{v,n}^{\min} + q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \]  \quad (B.2)

This constraint has to be fulfilled as a sufficient condition. The incentive rationality constraint states that when deciding to participate in the game the agent acts rational. This is the case if the agent’s utility function is positive or zero at minimum when participating in the game. This is expressed by (B.1). The proof is given by (B.3)–(B.4)

Equation (B.4) on the following page is derived from (B.1). The last expression of (B.4) gives that if the SOC of a certain PEV agent, \( soc_{v,n} \), is smaller than the expression on the right hand side, the agent will participate in the auction for energy and would act rational. The attained energy is expressed in terms of SOC and denoted through the variable \( q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \). The variable will take the value of the difference in SOC from the current SOC, denoted \( soc_{v,n}(T) \), to the one for which the utility function becomes zero in this time step. The dependence on \( T \) expresses that the energy is attained in one specific time step. The term \( \theta_{v,n}(T)|\Theta_n(T) \) expresses the dependence of the assigned energy on the agent’s individual energy valuation with respect to all other agents’ energy valuations at the same node \( n \).

Obviously, the participation is dependent on the current SOC of the agent and its valuation parameter. This is in accordance with the visualization of the utility function in Fig. 5.3 and Fig. 5.15.

An agent whose actual SOC is higher than the value given through the right hand side of (B.4) would act irrational if it would participate in the auction for energy/power because his marginal utility would be below the control price signal.
\[ u_{v,n}\left(T, \Omega(T), \pi_n(T), \theta_{v,n}(T)\right) \geq 0 \]
\[ \Leftrightarrow \theta_{v,n}(T)b_{v,n}\left(T, \Omega(T)\right) - \pi_n\left(T, \Theta_n(T)\right)C_{v,n}^B\theta_{v,n}(T) \geq 0 \]
\[ \Leftrightarrow \alpha_{v,n}(T)\theta_{v,n}(T)\Omega(T) - \beta_{v,n}(T)\theta_{v,n}(T)\left(\Omega(T)\right)^2 \geq \pi_n\left(T, \Theta_n(T)\right)C_{v,n}^B\theta_{v,n}(T) \geq 0 \]
\[ \Leftrightarrow \alpha_{v,n}(T)\theta_{v,n}(T)\Omega(T) - \beta_{v,n}(T)\theta_{v,n}(T)\left(\Omega(T)\right)^2 \geq \pi_n\left(T, \Theta_n(T)\right)C_{v,n}^B\left(\Omega(T) - soc_{v,n}(T) + soc_{v,n}^{\min}\right) \]

Knowing that \( \frac{\partial \Omega(T)}{\partial q_{v,n}(\cdot)} = 1 \) gives
\[ \Rightarrow \alpha_{v,n}(T)\theta_{v,n}(T) - 2\beta_{v,n}(T)\theta_{v,n}(T)\Omega(T) \geq \pi_n\left(T, \Theta_n(T)\right)C_{v,n}^B\theta_{v,n} \]
\[ \Leftrightarrow \alpha_{v,n}(T)\theta_{v,n}(T) - 2\beta_{v,n}(T)\theta_{v,n}(T)\left[soc_{v,n}(T) - soc_{v,n}^{\min} + q_{v,n}(T, \theta_{v,n}(T)\mid \Theta_n(T))\right] \geq \pi_n\left(T, \Theta_n(T)\right) \]
\[ \Leftrightarrow soc_{v,n}(T) + q_{v,n}(T, \theta_{v,n}(T)\mid \Theta_n(T)) \leq \frac{\alpha_{v,n}(T)\theta_{v,n}(T) - \pi_n\left(T, \Theta_n(T)\right)C_{v,n}^B}{2\beta_{v,n}(T)\theta_{v,n}(T)} + soc_{v,n}^{\min} \]

(B.4)
B.2 Proof of Incentive Compatibility for Utilizing the Revelation Theorem

The incentive compatibility constraint has to be proven as well in order to take advantage of the revelation theorem. Unfortunately, this is not as straightforward as the proof for incentive rationality. For incentive compatibility, the agent’s utility needs to be larger when the agent announces his true energy valuation in contrary to lying and announcing a wrong personal valuation. The latter is denoted $\hat{\theta}_{v,n}(T)$.

In the following, variables related to the situation where the agent acts untruthful are denoted with a hat, i.e., ($\hat{\cdot}$). The incentive compatibility condition is expressed as

$$
\begin{align*}
&u_{v,n}\left(q_{v,n}\left(T, \theta_{v,n}(T) | \Theta_n(T)\right), soc_{v,n}(T), soc_{v,n}^{\min}, \pi_n\left(T, \Theta_n(T)\right), \theta_{v,n}(T)\right) \\
&\quad \geq u_{v,n}\left(\hat{q}_{v,n}\left(T, \hat{\theta}_{v,n}(T) | \Theta_n(T)\right), soc_{v,n}(T), soc_{v,n}^{\min}, \hat{\pi}_n\left(T, \Theta_n(T)\right), \hat{\theta}_{v,n}(T)\right)
\end{align*}
$$

$$
\Leftrightarrow
$$

$$
\begin{align*}
&\theta_{v,n}(T)b_{v,n}\left(T, \Omega(T)\right) - \pi_n(T)q_{v,n}\left(T, \theta_{v,n}(T) | \Theta_n(T)\right) \\
&\quad \geq \hat{\theta}_{v,n}(T)b_{v,n}\left(T, \hat{\Omega}(T)\right) - \hat{\pi}_n(T)\hat{q}_{v,n}\left(T, \hat{\theta}_{v,n}(T) | \Theta_n(T)\right)
\end{align*}
$$

\(^{1}\text{It should be noted that } \hat{\Omega}(T) \text{ is derived from } \Omega(T) \text{ by using } \hat{q}_{v,n}\left(T, \hat{\theta}_{v,n}(T) | \Theta_n(T)\right) \text{ instead of } q_{v,n}\left(T, \theta_{v,n}(T) | \Theta_n(T)\right).\)
As a first possible situation at an electricity network node, it is assumed that the power for which the agents compete is not scarce, i.e., not constrained. Then, the announcement of an untruthful valuation parameter does not change the exogenous control price signal \( \pi_n(T) \). Furthermore, the attained energy amount of each agent is the same for the case of an untruthful or truthful announcement, hence:

\[
\hat{\pi}_n\left(T, \hat{\theta}_{v,n}(T) \mid \Theta_n(T)\right) C_{v,n}^B \hat{q}_{v,n}(\ldots) = \pi_n\left(T, \Theta_n(T)\right) C_{v,n}^B q_{v,n}(\ldots) = \pi_n\left(T, \Theta_n(T)\right) C_{v,n}^B q_{v,n}^{\text{max}}.
\]

Therefore, \( \pi_n(T) \) can be considered as the anticipated control price level outcome of an auction for energy/power among the PEV agents.

In this case, the PEV agents would not lie in any direction, i.e., they would not announce a higher and neither a lower valuation compared to the true value. In order to prove the incentive compatibility theorem, it can be stated that:

\[
\begin{align*}
\alpha_{v,n}(T) \theta_{v,n}(T) & \cdot \left[ \text{soc}_{v,n}(T) - \text{soc}_{v,n}^{\text{min}} + q_{v,n}\left(T, \theta_{v,n}(T) \mid \Theta_n(T)\right) \right] \\
-\beta_{v,n}(T) \theta_{v,n}(T) & \cdot \left[ \text{soc}_{v,n}(T) - \text{soc}_{v,n}^{\text{min}} + q_{v,n}\left(T, \theta_{v,n}(T) \mid \Theta_n(T)\right) \right]^2 \\
-\pi_n\left(T, \Theta_n(T)\right) & \cdot C_{v,n}^B q_{v,n}\left(T, \theta_{v,n}(T) \mid \Theta_n(T)\right) \\
& \geq \\
\alpha_{v,n}(T) \theta_{v,n}(T) & \cdot \left[ \text{soc}_{v,n}(T) - \text{soc}_{v,n}^{\text{min}} + q_{v,n}\left(T, \hat{\theta}_{v,n}(T) \mid \Theta_n(T)\right) \right] \\
-\beta_{v,n}(T) \theta_{v,n}(T) & \cdot \left[ \text{soc}_{v,n}(T) - \text{soc}_{v,n}^{\text{min}} + \hat{q}_{v,n}\left(T, \hat{\theta}_{v,n}(T) \mid \Theta_n(T)\right) \right]^2 \\
-\hat{\pi}_n\left(T, \hat{\theta}_{v,n}(T) \mid \Theta_n(T)\right) & \cdot C_{v,n}^B \hat{q}_{v,n}\left(T, \hat{\theta}_{v,n}(T) \mid \Theta_n(T)\right)
\end{align*}
\]

(B.8)
which is rearranged to

\[
\Leftrightarrow \quad 
\alpha_{v,n}(T) \theta_{v,n}(T) \cdot 
\begin{bmatrix}
soc_{v,n}(T) - soc_{v,n}^\min + q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \\
-soc_{v,n}(T) + soc_{v,n}^\min - \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T)|\Theta_n(T)) \\
+\beta_{v,n}(T) \theta_{v,n}(T) \cdot 
\begin{bmatrix}
(soc_{v,n}(T) - soc_{v,n}^\min + \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T)|\Theta_n(T)))^2 \\
-(soc_{v,n}(T) - soc_{v,n}^\min + q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)))^2 \\
+\hat{\pi}_n(T, \hat{\theta}_{v,n}(T)|\Theta_n(T)) \cdot C_B^{v,n} \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T)|\Theta_n(T)) \\
-\pi_n(T, \Theta_n(T)) \cdot C_B^{v,n} q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T))
\end{bmatrix} \\
+\hat{\pi}_n(T, \hat{\theta}_{v,n}(T)|\Theta_n(T)) \cdot C_B^{v,n} \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T)|\Theta_n(T)) \\
-\pi_n(T, \Theta_n(T)) \cdot C_B^{v,n} q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \\
\geq 0
\end{bmatrix}
\geq 0
\]

(B.9)
B.2. Proof of Incentive Compatibility

\[
\begin{align*}
&\iff \\
&\left( \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T) | \Theta_n(T)) - q_{v,n}(T, \theta_{v,n}(T) | \Theta_n(T)) \right) \\
&\left[ \pi_n(T, \Theta_n(T)) C_v^n + \theta_{v,n}(T) \left( -\alpha_{v,n}(T) + 2\beta_{v,n}(T)(soc_{v,n}(T) - soc_{v,n}^\text{min}) \right) \right. \\
&\left. + \theta_{v,n}(T) \left( \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T) | \Theta_n(T)) + q_{v,n}(T, \theta_{v,n}(T) | \Theta_n(T)) \right) \right] \geq 0 
\end{align*}
\]

(B.11)

when using (B.4) it can be followed that

\[
\begin{align*}
&\implies \\
&\left( q_{v,n}(T, \theta_{v,n}(T) | \Theta_n(T)) - \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T) | \Theta_n(T)) \right) \cdot (-1). \\
&\left[ \pi_n(T, \Theta_n(T)) C_v^n + \theta_{v,n}(T) \left( -\alpha_{v,n}(T) + 2\beta_{v,n}(T)(soc_{v,n}(T) - soc_{v,n}^\text{min}) \right) \right. \\
&\left. + \theta_{v,n}(T) \left( \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T) | \Theta_n(T)) + q_{v,n}(T, \theta_{v,n}(T) | \Theta_n(T)) \right) \right] \geq \\
&\left( q_{v,n}(T, \theta_{v,n}(T) | \Theta_n(T)) - \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T) | \Theta_n(T)) \right) . \\
&2\beta_{v,n}(T) \theta_{v,n}(T) q_{v,n}(T, \theta_{v,n}(T) | \Theta_n(T)) - \beta_{v,n}(T) \theta_{v,n}(T). \\
&\left( q_{v,n}(T, \theta_{v,n}(T) | \Theta_n(T)) + \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T) | \Theta_n(T)) \right) \geq 0 
\end{align*}
\]

(B.12)

and

\[
\begin{align*}
&\implies \\
&\left[ 2\beta_{v,n}(T) \theta_{v,n}(T) q_{v,n}(T, \theta_{v,n}(T) | \Theta_n(T)) - \beta_{v,n}(T) \theta_{v,n}(T). \right. \\
&\left( q_{v,n}(T, \theta_{v,n}(T) | \Theta_n(T)) + \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T) | \Theta_n(T)) \right) = \\
&\left( q_{v,n}(T, \theta_{v,n}(T) | \Theta_n(T)) - \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T) | \Theta_n(T)) \right) \beta_{v,n}(T) \theta_{v,n}(T). \\
&\left( q_{v,n}(T, \theta_{v,n}(T) | \Theta_n(T)) - \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T) | \Theta_n(T)) \right) \geq 0
\end{align*}
\]

(B.13)
and finally
\[ \Rightarrow \]
\[ \beta_{v,n}(T)\theta_{v,n}(T) \left( q_{v,n}(T,\theta_{v,n}(T)|\Theta_n(T)) - \hat{q}_{v,n}(T,\hat{\theta}_{v,n}(T)|\Theta_n(T)) \right)^2 \geq 0 \]
\textit{q.e.d.} \hfill \text{(B.14)}

Expression (B.14) is always true since each factor is positive.

The situation when the good is unconstrained and always available for the agents is visualized in Fig. B.1. There, the ordinate plots the weighted marginal benefit of a PEV agent and the abscissa plots the amount of charging power which the agents receives as a result from the auction. The maximum power is limited by the physical network connection denoted as \( q_{v,n}^{\text{max}} \).

Figure B.1(a) displays the situation where the PEV agent announces his true valuation \( \theta_{v,n}(T) \) in an exogenously given, constant control price scenario. The PEV agent incorporates a SOC which gives that the agent’s utility function intersects the exogenous control price level. As power is not limited at the location and the objective of the auction among the agents is to maximize the agents total utility, an auctioneer will maximize the area between the exogenous control price level \( \pi_n(T) \) and the marginal benefit weighted by the announced personal valuation. The latter is the solid line with the ordinate intercept at \( \theta_{v,n}(T)\alpha_{v,n}(T) \).

For the case where the PEV agent announced its true valuation, the agent receives the largest utility, visualized by the area \( A_{\theta_{v,n}} \).

Figure B.1(b) displays the outcome of the auction for the same PEV agent but with its untruthful announcement of a higher personal valuation, denoted \( \hat{\theta}_{v,n}(T) \). In this case, the agent receives more power but its final utility, as can be noticed, is smaller than for a truthful announcement. The part of the orange area which lies under the horizontal line corresponding to \( \pi_n(T) \), reduces the total utility of the agent. Therefore, the agent would not announce a higher personal valuation in a system state where the charging power is unlimited.

Figure B.1(c) shows the outcome for the untruthful announcement of a lower personal valuation. In this case, the agent receives a lower utility as visualized by the area \( A_{\hat{\theta}_{v,n}} \) which is smaller than the area displayed in Fig. B.1(a).
B.2. Proof of Incentive Compatibility

Figure B.1: Comparison between the PEV agent’s utility for different strategies of announcing the personal parameter $\theta_{v,n}(T)$. Figure B.1(a) shows the utility for announcing the true value $q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T))$. Figure B.1(b) shows the utility for an untrue but bigger value, Fig. B.1(c) for an untrue but lower value. The situation depicts a case where the weighted marginal utility intersects the exogenous control price signal at a point between 0 and $q_{v,n}^{\max}$. The control price level $\pi_n(T)$ is not altered by the individual agent announcements (according to (B.7)-(B.14)).
It should be noted that the proof, given by equations (B.6)–(B.14), does not consider that the energy $q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T))$, which can be acquired in the auction, is limited by the physical power connection. The proof further assumes that the control price level intersects the weighted marginal benefit. In fact, this does not have to be the case because a PEV agent can have a low SOC, i.e., a high utility function value, and even charging at the maximum, physically possible power $q_{v,n}^{max}$ does not result in the intersection of exogenous control price signal level and the weighted marginal benefit. In such a case, the agent could announce an untruthful personal valuation. However, this would not be of interest. The agent would not be able to take a strategic advantage out of this behavior because it would not effect the outcome in this situation. In the unlimited resource situation studied here, the agent would receive the maximum charging power in any case, i.e., whether announcing the personal valuation truthfully or not. Furthermore, the agent would not be able to influence the given system control price signal.

**Case 2**

If case 1 is not true, the control price signal will change. The control price change is, in this case, dependent on the announcements of the PEV agents. For such a case the following can be stated:

\[
\Rightarrow \\
\alpha_{v,n}(T)\theta_{v,n}(T) \cdot \left[ q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) - \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T)|\Theta_n(T)) \right] \\
+\beta_{v,n}(T)\theta_{v,n}(T) \cdot \left[ 2soc_{v,n}(T) \cdot \left( \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T)|\Theta_n(T)) - q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \right) - 2soc_{v,n}^{min} \cdot \left( \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T)|\Theta_n(T)) - q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \right) + \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T)|\Theta_n(T))^2 - q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T))^2 \right] \\
+C_{v,n}^B \cdot \left[ \hat{\pi}_n(T, \hat{\theta}_{v,n}(T)|\Theta_n(T))\hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T)|\Theta_n(T)) - \pi_n(T, \Theta_n(T))q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \right] \geq 0
\]  

(B.15)
which is rearranged to

\[ \Leftrightarrow \]

\[ \hat{q}_{v,n}(T,\hat{\theta}_{v,n}(T)|\Theta_n(T)) \cdot \left[ \hat{\pi}_{n}(T,\hat{\theta}_{v,n}(T)|\Theta_n(T))C_{v,n}^B - \alpha_{v,n}(T)\theta_{v,n}(T) \right. \]

\[ + 2\beta_{v,n}(T)\theta_{v,n}(T)(soc_{v,n}(T) - soc_{v,n}^{\text{min}}) \]

\[ - q_{v,n}(T,\theta_{v,n}(T)|\Theta_n(T)) \cdot \left[ \left( T,\Theta_n(T) \right)C_{v,n}^B + \alpha_{v,n}(T)\theta_{v,n}(T) \right. \]

\[ - 2\beta_{v,n}(T)\theta_{v,n}(T)(2soc_{v,n}(T) - 2soc_{v,n}^{\text{min}}) \]

\[ + \beta_{v,n}(T)\theta_{v,n}(T) \cdot \left[ \hat{q}_{v,n}(T,\hat{\theta}_{v,n}(T)|\Theta_n(T))^2 \right. \]

\[ - q_{v,n}(T,\hat{\theta}_{v,n}(T)|\Theta_n(T))^2 \geq 0 \]

(B.16)

and with

\[ -2\beta_{v,n}(T)q_{v,n}(T,\theta_{v,n}(T)|\Theta_n(T)) \geq \pi(T,\Theta_n(T))C_{v,n}^B \]

\[ - \theta_{v,n}(T)\alpha_{v,n}(T) + 2\beta_{v,n}(T)soc_{v,n}(T) - 2\beta_{v,n}(T)soc_{v,n}^{\text{min}} \]

\[ \Rightarrow \]

(B.17)
it follows that

\[
\hat{q}_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \cdot \left[ \hat{\pi}_n(T, \hat{\theta}_{v,n}(T)|\Theta_n(T)) C_{v,n}^B - \alpha_{v,n}(T)\theta_{v,n}(T) \\
+ 2\beta_{v,n}(T)\theta_{v,n}(T)(soc_{v,n}(T) - soc_{v,n}^{min}) \right] \\
- q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \cdot \left[ \pi_n(T, \Theta_n(T)) C_{v,n}^B - \alpha_{v,n}(T)\theta_{v,n}(T) \\
+ 2\beta_{v,n}(T)\theta_{v,n}(T)(2soc_{v,n}(T) - 2soc_{v,n}^{min}) \right] \\
+ \beta_{v,n}\theta_{v,n}(T) \cdot \left[ \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T)|\Theta_n(T))^2 \\
- q_{v,n}(T, \hat{\theta}_{v,n}(T)|\Theta_n(T))^2 \right] \geq 0
\]

\[
\hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T)|\Theta_n(T)) \cdot \left[ \hat{\pi}_n(T, \hat{\theta}_{v,n}(T)|\Theta_n(T)) C_{v,n}^B - \alpha_{v,n}(T)\theta_{v,n}(T) \\
+ 2\beta_{v,n}(T)\theta_{v,n}(T)(soc_{v,n}(T) - soc_{v,n}^{min}) \right] \\
- q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \cdot \left[ -2\beta_{v,n}(T)\theta_{v,n}(T)q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \\
+ \beta_{v,n}(T)\theta_{v,n}(T) \cdot \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T)|\Theta_n(T))^2 \\
- q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T))^2 \right] \geq 0
\]

which can be also rearranged to

\[
\Leftrightarrow \hat{\pi}_n(T, \hat{\theta}_{v,n}(T)|\Theta_n(T)) C_{v,n}^B \\
- \theta_{v,n}(T)\alpha_{v,n}(T) + 2\theta_{v,n}(T)\beta_{v,n}(T)(soc_{v,n}(T) - soc_{v,n}^{min}) \geq \\
- \beta_{v,n}(T)\theta_{v,n}(T)q_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T))^2 + \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T)|\Theta_n(T))^2 \\
\left[ \hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T)|\Theta_n(T)) \right]^2 \leq 0
\]
B.2. Proof of Incentive Compatibility

Furthermore,

\[ \pi_n(T, \hat{\theta}_{v,n}(T)|\Theta_n(T)) C_{v,n}^B \geq \alpha_{v,n}(T)\theta_{v,n}(T) - 2\beta_{v,n}(T)\theta_{v,n}(T) \text{soc}_{v,n}(T) + 2\beta_{v,n}(T)\theta_{v,n}(T) \text{soc}^{\min}_{v,n} \]

\[ -\beta_{v,n}(T)\theta_{v,n} \frac{q_{v,n}(T,\theta_{v,n}(T)|\Theta_n(T)) + \hat{q}_{v,n}(T,\hat{\theta}_{v,n}(T)|\Theta_n(T))}{2\hat{q}_{v,n}(T,\hat{\theta}_{v,n}(T)|\Theta_n(T))} \]

(B.20)

and therefore

\[ \pi(T, \hat{\theta}_{v,n}(T)|\Theta_n(T)) C_{v,n}^B \geq \alpha_{v,n}(T)\theta_{v,n}(T) - 2\beta_{v,n}(T)\theta_{v,n}(T) \left[ \text{soc}_{v,n}(T) - \text{soc}^{\min}_{v,n} \right] \]

\[ + \frac{q_{v,n}(T,\theta_{v,n}(T)|\Theta_n(T)) + \hat{q}_{v,n}(T,\hat{\theta}_{v,n}(T)|\Theta_n(T))}{2\hat{q}_{v,n}(T,\hat{\theta}_{v,n}(T)|\Theta_n(T))} \]

(B.21)

The proof states that the control price increase in a congested case should be according to the expression given in (B.21) in order to fulfill the incentive compatibility constraint.

Figure B.2 illustrates a situation when the total available power for charging is scarce at a location \( n \). Thus, the PEV agents cannot be allowed to receive their desired demands as they would congest the network. This situation gives rise to strategic behavior and shows the situation modeled through the proof given above.

For the analysis of this situation and to illustrate the equations given in the proof, it is assumed that the weighted marginal benefit of the PEV agent does not intersect the exogenously given control price level \( \pi_n(T) \). The assumption is incorporated in (B.15)-(B.21). Equation (B.21) shows that in order to fulfill the incentive compatibility constraint, the control price signal markup for an agent, which untruthfully announces his personal valuation parameter, should be the mean of the squared energy amounts received in the two cases, i.e., for announcing it truthfully and untruthfully. This means that the control price asked from every individual agent would need to be different. Furthermore, in both untrue cases, i.e., lying upwards or downwards, the individually asked control price would need to rise. This complex situation is shown in Fig. B.2.
Figure B.2(a) shows the situation and a potential outcome of the auction when the PEV agent truthfully announces its personal valuation parameter. The agent then receives the utility $A_{\theta_{v,n}}$ which is indicated by the green area. However, if the behavior of the other agents should lead to a control price outcome of $\hat{\pi}_{n1}(T)$, the depicted agent receives a smaller, total utility because the control price increased.

Figure B.2(b) displays the situation when the PEV agent untruthfully announces a higher personal valuation. In this case, the agent could potentially receive more energy $\hat{q}_{v,n}(T, \hat{\theta}_{v,n}(T)|\Theta_{n}(T))$ than when announcing the true personal valuation and thus achieve a higher utility value. However, this is dependent on the announcement of the PEV agent’s $\theta_{v,n}(T)$ in relation to the announcements of all other agents, as indicated by the dependency on $\Theta_{n}(T)$.

The untruthful announcement of the agent could influence the control price signal and increase it to $\hat{\pi}_{n1}(T)$. Then, the agent could receive more energy than when acting truthfully. Depending on how much the control price would rise, the utility could either be larger or smaller as compared to the situation shown in Fig. B.2(a). The possibility of actually loosing utility through the strategic behavior of the other agents in response to the behavior of the depicted agent is visualized by the blue area. The area indicates the loss in utility due to the increased control price signal level.

Figure B.2(c) illustrates the situation when the agent announces an untruthful and low personal valuation $\hat{\theta}_{v,n}''(T)$. Then, the agent could receive less charging power compared to the case displayed in Fig. B.2(a). However, this case can be neglected due to the following argumentation:

The PEV agents do not know whether they bid for a scarce, i.e., constrained good, or whether the good is unlimitedly available, i.e., there is enough power available for all connected agents. The reason for this is simple. The individual PEV agent cannot know whether there is a congestion at the specific network node and at the specific time when he is connected. This information is usually not available for him.
B.2. Proof of Incentive Compatibility

Figure B.2: Comparison between PEV agent’s utility for different strategies of announcing $\theta_{v,n}(T)$. Figure B.2 (a) shows the utility for announcing the true value, Fig. B.2(b) shows the utility for a bigger and Fig. B.2(c) for a lower value. Here, a situation is depicted where the weighted marginal utility does not intersect the given control price signal level and thus gives rise to strategic behavior. The strategic behavior can influence the control price outcome which is illustrated by the dash-dotted lines (according to (B.15)-(B.21)).
The information on the state of the complete system is only available to a different entity such as the PEV aggregator or the DisCo\textsuperscript{2}. If agents assume they bid for an unconstrained good, a PEV agent would generally not announce a lower personal valuation\textsuperscript{3}.

It is found that the incentive compatibility constraint cannot be sufficiently proven for all possible agent bidding using the designed mechanism. However, given the assumption that the agent’s notion is to always bid for an unconstrained good, the agent would not lie. This includes even the situation where the good is scarce, and the agent’s weighted marginal benefit intersects the exogenous control price signal, as proven through (B.6)-(B.14).

Those agents, whose weighted marginal benefit does not intersect the control price signal $\pi_n(T)$, can be restricted in their strategic behavior. Strategic behavior is always encountered when the number of agents is small [122]. In the case of PEV agents gaming for power, this is often not the case. It can assumed that large numbers of PEV agents are bidding for a potentially scarce resource. This is realistic as large numbers of PEVs are needed to congest a substation or a transformer station in the medium voltage network\textsuperscript{4}. Large numbers are easily reached as low voltage sub-networks span and supply large geographical areas. Thus, with good approximation, it is even feasible to assume perfect competition. If perfect competition holds it can be followed that agents, whose weighted marginal benefit does not intersect the given control price level, will not behave strategically. Hence, subsequently, truthfully announcing the personal valuation becomes a dominant strategy\textsuperscript{5}.

\textsuperscript{2}The system state is constantly changing due to temporal and spatial varying loads, to switch states, and to the number of connected PEVs, etc. One network node can be congested during one time interval while in the next time interval it could offer an unconstrained power supply.

\textsuperscript{3}It is assumed that the system state information is not transmitted to every connected PEV agent as it could contain critical parts which could be exploited.

\textsuperscript{4}The electricity networks are usually overdimensioned, especially on lower network levels, e.g. in cities.

\textsuperscript{5}In fact, the assumption of perfect competition is far-ranging and crucial. It removes strategic behavior completely from the problem formulation. In order to avoid this far-ranging assumption, a different mechanism using a different utility function would need to be designed. Such an utility function should not suffer from special cases like the ones described above but should describe an agent behavior which is rational in the sense as it was argued for the benefit function. The function herein was defined in relation to well know electricity market concepts and their consumer modeling. However, finding such utility function is out of scope for this thesis.
Appendix C

Lagrangian Function and KKT Constraints for the PEV Manager

Lagrange function:

\[
L_n = \sum_{v=1}^{N_n^V(T)} \theta_{v,n}(T).
\]

\[
\left[ \alpha_{v,n}(T)C_{v,n}^B \left( soc_{v,n}(T) - soc_{v,n}^\text{min} + \frac{1}{\zeta(T)}C_{v,n} p_{v,n}(T,\theta_{v,n}(T)|\Theta_n(T)) \right) \\
- \beta_{v,n}(T)C_{v,n}^B \left( soc(T)_{v,n} - soc_{v,n}^\text{min} + \frac{1}{\zeta(T)}C_{v,n} p_{v,n}(T,\theta_{v,n}(T)|\Theta_n(T)) \right)^2 \\
- \pi_n(T,\Theta_n(T))C_{v,n}^B \frac{1}{\zeta(T)}C_{v,n} p_{v,n}(T,\theta_{v,n}(T)|\Theta_n(T)) \\
- \sum_{v=1}^{N_n^V(T)} \mu_{v,n}^\text{upp}(T) \left[ p_{v,n}(T,\theta_{v,n}(T)|\Theta_n(T)) - p_{v,n}^\text{max}(T) \right] \\
+ \sum_{v=1}^{N_n^V(T)} \mu_{v,n}^\text{low}(T) \left[ p_{v,n}(T,\theta_{v,n}(T)|\Theta_n(T)) + p_{v,n}^\text{min}(T) \right] \\
- \sigma_n^\text{upp}(T) \left[ \sum_{v=1}^{N_n^V(T)} p_{v,n}(T,\theta_{v,n}(T)|\Theta_n(T)) - P_n^\text{max}(T) \right] \\
+ \sigma_n^\text{low}(T) \left[ \sum_{v=1}^{N_n^V(T)} p_{v,n}(T,\theta_{v,n}(T)|\Theta_n(T)) + P_n^\text{min}(T) \right]
\]  

(C.1)
Karush-Kuhn-Tucker equations:

\[
\frac{dL_n}{dp_{v,n}(T)}|_{\hat{p}_{v,n}(T), \hat{\mu}_{v,n}(T), \hat{\sigma}_{v,n}(T)} = \theta_{v,n}(T) \left[ \alpha_{v,n}(T) - 2\beta_{v,n}(T) \left( soc_{v,n}(T) - soc_{v,n}^{\min} + \frac{1}{\xi(T)C_{v,n}} p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \right) \right] - \\
\pi_n(T)\frac{1}{\xi(T)} - \mu_{v,n}^{\text{upp}}(T) + \mu_{v,n}^{\text{low}}(T) - \sigma_n^{\text{upp}}(T) + \sigma_n^{\text{low}}(T) = 0 \quad (C.2a)
\]

\[
\mu_{v,n}^{\text{upp}}(T) \frac{dL_n}{d\mu_{v,n}^{\text{upp}}(T)}|_{\hat{p}_{v,n}(T), \hat{\mu}_{v,n}(T), \hat{\sigma}_{v,n}(T)} = \mu_{v,n}^{\text{upp}}(T) \left[ p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) - p_{v,n}^{\max}(T) \right] = 0 \quad (C.2b)
\]

\[
\mu_{v,n}^{\text{low}}(T) \frac{dL_n}{d\mu_{v,n}^{\text{low}}(T)}|_{\hat{p}_{v,n}(T), \hat{\mu}_{v,n}(T), \hat{\sigma}_{v,n}(T)} = \mu_{v,n}^{\text{low}}(T) \left[ - p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) + p_{v,n}^{\min}(T) \right] = 0 \quad (C.2c)
\]

\[
\sigma_{v,n}^{\text{upp}}(T) \frac{dL_n}{d\sigma_{v,n}^{\text{upp}}(T)}|_{\hat{p}_{v,n}(T), \hat{\mu}_{v,n}(T), \hat{\sigma}_{v,n}(T)} = \sigma_{v,n}^{\text{upp}}(T) \left[ \sum_{v=1}^{N_n(T)} p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) - P_n^{\max}(T) \right] = 0 \quad (C.2d)
\]

\[
\sigma_{v,n}^{\text{low}}(T) \frac{dL_n}{d\sigma_{v,n}^{\text{low}}(T)}|_{\hat{p}_{v,n}(T), \hat{\mu}_{v,n}(T), \hat{\sigma}_{v,n}(T)} = \sigma_{v,n}^{\text{low}}(T) \left[ - \sum_{v=1}^{N_n(T)} p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) + P_n^{\min}(T) \right] = 0 \quad (C.2e)
\]

\[
\frac{dL_n}{d\mu_{v,n}^{\text{upp}}(T)}|_{\hat{p}_{v,n}(T)} = p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) - p_{v,n}^{\max}(T) \leq 0 \quad (C.2f)
\]

\[
\frac{dL_n}{d\mu_{v,n}^{\text{low}}(T)}|_{\hat{p}_{v,n}(T)} = -p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) + p_{v,n}^{\min}(T) \leq 0 \quad (C.2g)
\]
\[
\frac{dL_n}{d\sigma_{v,n}^{\text{upp}}}(T) \bigg|_{\hat{p}_{v,n}(T)} = \sum_{v=1}^{N^V(T)} p_v(T, \theta_{v,n}(T)|\Theta_n(T)) - P_n^{\text{max}}(T) \leq 0 \quad (C.2h)
\]

\[
\frac{dL_n}{d\sigma_{v,n}^{\text{low}}}(T) \bigg|_{\hat{p}_{v,n}(T)} = -\sum_{v=1}^{N^V(T)} p_v(T, \theta_{v,n}(T)|\Theta_n(T)) + P_n^{\text{min}}(T) \leq 0 \quad (C.2i)
\]

\[
\mu_{v,n}^{\text{upp}}(T) \geq 0 \quad (C.2j)
\]

\[
\mu_{v,n}^{\text{low}}(T) \geq 0 \quad (C.2k)
\]

\[
\sigma_{v,n}^{\text{upp}}(T) \geq 0 \quad (C.2l)
\]

\[
\sigma_{v,n}^{\text{low}}(T) \geq 0 \quad (C.2m)
\]

Hence the price after optimization for a particular amount of cars in T is determined by the \( \sigma^{\text{upp}} \) constraints:

\[
\theta_{v,n}(T) \left[ \alpha_{v,n}(T) \frac{1}{\varsigma(T)} - 2\beta_{v,n}(T) \frac{1}{\varsigma(T)} \left( \text{soc}_{v,n}(T) - \text{soc}_{v,n}^{\text{min}} + \frac{1}{\varsigma(T)} c_{v,n} \right) \right] - \mu_{v,n}^{\text{upp}}(T) + \mu_{v,n}^{\text{low}}(T) = \\
\pi_n(T) \frac{1}{\varsigma(T)} + \sigma_n^{\text{upp}}(T) - \sigma_n^{\text{low}}(T)
\]

\[
\theta_{v,n}(T) \left[ \alpha_{v,n}(T) - 2\beta_{v,n}(T) \left( \text{soc}_{v,n}(T) - \text{soc}_{v,n}^{\text{min}} + \frac{1}{\varsigma(T)} c_{v,n} \right) \right] - \frac{\varsigma(T)}{T} \left[ \mu_{v,n}^{\text{upp}}(T) + \mu_{v,n}^{\text{low}}(T) \right] = \\
\pi_n(T) + \frac{\varsigma(T)}{T} \left[ \sigma_n^{\text{upp}}(T) - \sigma_n^{\text{low}}(T) \right]
\]

\[
\Rightarrow \\
\pi_n(T) + \frac{\varsigma(T)}{T} \left[ \sigma_n^{\text{upp}}(T) - \sigma_n^{\text{low}}(T) \right]
\]

Nodal PEV recharging control price signal at \( n \)
Appendix D

Lagrange Function and Constraints of the Predictive PEV Manager
Lagrange function for MPC Manager optimization:

\[
L_n = \sum_{t=T}^{T+\Delta T_n^{RH}} \sum_{v=1}^{N_n^V(T)} \theta_{v,n}(t) \\
\left[ \alpha_{v,n}(t)C_{v,n}^B \left( soc_{v,n}(t) - soc_{v,n}^{\min} + \frac{1}{\varsigma(t)C_{v,n}^B} p_{v,n}(t, \theta_{v,n}(t)|\Theta_n(t)) \right) \right. \\
- \beta_{v,n}(t)C_{v,n}^B \left( soc_{v,n}(t) - soc_{v,n}^{\min} + \frac{1}{\varsigma(t)C_{v,n}^B} p_{v,n}(t, \theta_{v,n}(t)|\Theta_n(t)) \right)^2 \\
- \pi_n(t)C_{v,n}^B \frac{1}{\varsigma(t)C_{v,n}^B} p_{v,n}(t, \theta_{v,n}(t)|\Theta_n(t)) \\
+ \sum_{t=T}^{T+\Delta T_n^{RH}} \sum_{v \in V_n(t)} \mu_{v,n}^{upp,1}(t) \left[ p_{v,n}(t, \theta_{v,n}(t)|\Theta_n(t)) - p_{v,n}^{\max}(t) \right] \\
+ \sum_{t=T}^{T+\Delta T_n^{RH}} \sum_{v \in V_n(t)} \mu_{v,n}^{low,1}(t) \left[ p_{v,n}^{\min}(t) - p_{v,n}(t, \theta_{v,n}(t)|\Theta_n(t)) \right] \\
+ \mu_{v,n}^{low,2}(t) \left[ soc_{v,n}^{\min} - soc_{v,n}(t) - \frac{1}{\varsigma(t)C_{v,n}^B} p_{v,n}(t, \theta_{v,n}(t)|\Theta_n(t)) \right] \\
+ \mu_{v,n}^{upp,2}(t) \left[ soc_{v,n}(t) + \sum_{t=T}^{T+\Delta T_n^{RH}} \frac{1}{\varsigma(t)C_{v,n}^B} p_{v,n}(t, \theta_{v,n}(t)|\Theta_n(t)) - soc_{v,n}^{\max} \right] \\
+ \sum_{t=T}^{T+\Delta T_n^{RH}} \sigma_{n}^{upp}(t) \left[ \sum_{v \in V_n(t)} p_{v,n}(t, \theta_{v,n}(t)|\Theta_n(t)) - P_{n}^{\max}(t) \right] \\
+ \sum_{t=T}^{T+\Delta T_n^{RH}} \sigma_{n}^{low}(t) \left[ P_{n}^{\min}(t) - \sum_{v \in V_n(t)} p_{v,n}(t, \theta_{v,n}(t)|\Theta_n(t)) \right] \tag{D.1}
\]
Karush-Kuhn-Tucker equations of an MPC PEV Manager. Here, for simplicity, an MPC horizon $T_{RH}^n = 1$ is assumed:

\[
d\frac{L_n}{dp_{v,n}(T)}|_{\dot{p}_{v,n}(T), \dot{\mu}_{v,n}(T), \dot{\sigma}_{v,n}(T)} =
\]

\[\theta_{v,n}(T) \left[ \alpha_{v,n}(T) \frac{1}{\zeta(T)} - 2 \beta_{v,n}(T) \frac{1}{\zeta(T)} \left( soc_{v,n}(T) - soc_{v,n}^{min} + \frac{1}{\zeta(T) C_{v,n}} p_{v,n} \left( T, \theta_{v,n}(T)|\Theta_{n}(T) \right) \right) \right] - \pi_{n}(T) \frac{1}{\zeta(T)}
\]

\[+ \theta_{v,n}(T+1) \left[ \alpha_{v,n}(T) \frac{1}{\zeta(T)} - 2 \beta_{v,n}(T) \frac{1}{\zeta(T)} \left( soc_{v,n}(T+1) - soc_{v,n}^{min} + \frac{1}{\zeta(T) C_{v,n}} p_{v,n} \left( T+1, \theta_{v,n}(T+1)|\Theta_{n}(T+1) \right) \right) \right]
\]

\[+ \mu_{v,n}^{upp,1}(T) - \mu_{v,n}^{low,1}(T) + \mu_{v,n}^{upp,1}(T+1) - \mu_{v,n}^{low,1}(T+1)
\]

\[+ \mu_{v,n}^{upp,2}(T) - \mu_{v,n}^{low,2}(T) + \mu_{v,n}^{upp,2}(T+1) - \mu_{v,n}^{low,2}(T+1)
\]

\[+ \sigma_{v,n}^{upp}(T) - \sigma_{v,n}^{low}(T) + \sigma_{v,n}^{upp}(T+1) - \sigma_{v,n}^{low}(T+1)
\]

\[= 0 \ (D.2a)
\]

\[\mu_{v,n}^{upp,1}(T) \frac{dL_n}{d\mu_{v,n}^{upp,1}(T)}|_{\dot{p}_{v,n}(T), \dot{\mu}_{v,n}^{upp,1}(T)} =
\]

\[\mu_{v,n}^{upp,1}(T) \left[ p_{v,n} \left( T, \theta_{v,n}(T)|\Theta_{n}(T) \right) - p_{v,n}^{max}(T) \right]
\]

\[= 0 \ (D.2b)
\]

\[\mu_{v,n}^{upp,1}(T+1) \frac{dL_n}{d\mu_{v,n}^{upp,1}(T+1)}|_{\dot{p}_{v,n}(T+1), \dot{\mu}_{v,n}^{upp,1}(T+1)} =
\]

\[\mu_{v,n}^{upp,1}(T+1) \left[ p_{v,n} \left( T+1, \theta_{v,n}(T+1)|\Theta_{n}(T+1) \right) - p_{v,n}^{max}(T+1) \right]
\]

\[= 0 \ (D.2c)
\]

\[\mu_{v,n}^{low,1}(T) \frac{dL_n}{d\mu_{v,n}^{low,1}(T)}|_{\dot{p}_{v,n}(T), \dot{\mu}_{v,n}^{low,1}(T)} =
\]

\[\mu_{v,n}^{low,1}(T) \left[ p_{min}^{min}(T) - p_{v,n} \left( T, \theta_{v,n}(T)|\Theta_{n}(T) \right) \right]
\]

\[= 0 \ (D.2d)
\]
\[ \mu_{v,n}^{\text{low},1}(T + 1) \frac{dL_n^{\text{low},1}(T+1)}{d\mu_{v,n}^{\text{low},1}(T+1)} |_{\hat{p}_{v,n}(T+1),\hat{\mu}_{v,n}^{\text{low},1}(T+1)} = \\
\mu_{v,n}^{\text{low},1}(T + 1) \left[ p_{v,n}^{\text{min}}(T + 1) - p_{v,n}(T + 1, \theta_{v,n}(T+1)|\Theta_{n}(T+1)) \right] = 0 \ (D.2e) \]

\[ \mu_{v,n}^{\text{upp},2}(T) \frac{dL_n^{\text{upp},2}(T)}{d\mu_{v,n}^{\text{upp},2}(T)} |_{\hat{p}_{v,n}(T),\hat{\mu}_{v,n}^{\text{upp},2}(T)} = \\
\mu_{v,n}^{\text{upp},2}(T) \left[ soc_{v,n}(T) + \frac{1}{\varsigma(T)C_{v,n}^B} p_{v,n}(T, \theta_{v,n}(T)|\Theta_{n}(T)) - soc_{v,n}^{\text{max}} \right] = 0 \ (D.2f) \]

\[ \mu_{v,n}^{\text{upp},2}(T + 1) \frac{dL_n^{\text{upp},2}(T+1)}{d\mu_{v,n}^{\text{upp},2}(T+1)} |_{\hat{p}_{v,n}(T+1),\hat{\mu}_{v,n}^{\text{upp},2}(T+1)} = \\
\mu_{v,n}^{\text{upp},2}(T + 1) \left[ soc_{v,n}(T) + \sum_{t=T}^{T+1} \frac{1}{\varsigma(t)C_{v,n}^B} p_{v,n}(t, \theta_{v,n}(t)|\Theta_{n}(t)) - soc_{v,n}^{\text{max}} \right] = 0 \ (D.2g) \]

\[ \mu_{v,n}^{\text{low},2}(T) \frac{dL_n^{\text{low},2}(T)}{d\mu_{v,n}^{\text{low},2}(T)} |_{\hat{p}_{v,n}(T),\hat{\mu}_{v,n}^{\text{low},2}(T)} = \\
\mu_{v,n}^{\text{low},2}(T) \left[ soc_{v,n}^{\text{min}} - soc_{v,n}(T) - \frac{1}{\varsigma(T)C_{v,n}^B} p_{v,n}(T, \theta_{v,n}(T)|\Theta_{n}(T)) \right] = 0 \ (D.2h) \]

\[ \mu_{v,n}^{\text{low},2}(T + 1) \frac{dL_n^{\text{low},2}(T+1)}{d\mu_{v,n}^{\text{low},2}(T+1)} |_{\hat{p}_{v,n}(T+1),\hat{\mu}_{v,n}^{\text{low},2}(T+1)} = \\
\mu_{v,n}^{\text{low},2}(T + 1) \left[ soc_{v,n}^{\text{min}} - soc_{v,n}(T) - \sum_{t=T}^{T+1} \frac{1}{\varsigma(t)C_{v,n}^B} p_{v,n}(t, \theta_{v,n}(t)|\Theta_{n}(t)) \right] = 0 \ (D.2i) \]
\[
\sigma_{v,n}(T) \frac{dL_n}{d\sigma_{v,n}(T)} |_{\tilde{p}_{v,n}(T), \tilde{\sigma}_{v,n}(T)} = \sigma_{v,n}(T) \left[ \sum_{v=1}^{N_n(T)} p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) - P_{n}^{\text{max}}(T) \right] = 0 \quad (D.2j)
\]

\[
\sigma_{v,n}(T+1) \frac{dL_n}{d\sigma_{v,n}(T+1)} |_{\tilde{p}_{v,n}(T+1), \tilde{\sigma}_{v,n}(T+1)} = \sigma_{v,n}(T+1) \left[ \sum_{v=1}^{N_n(T+1)} p_{v,n}(T+1, \theta_{v,n}(T+1)|\Theta_n(T+1)) - P_{n}^{\text{max}}(T+1) \right] = 0 \quad (D.2k)
\]

\[
\sigma_{v,n}(T) \frac{dL_n}{d\sigma_{v,n}(T)} |_{\tilde{p}_{v,n}(T), \tilde{\sigma}_{v,n}(T)} = \sigma_{v,n}(T) \left[ P_{n}^{\text{min}}(T) - \sum_{v=1}^{N_n(T)} p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \right] = 0 \quad (D.2l)
\]

\[
\sigma_{v,n}(T+1) \frac{dL_n}{d\sigma_{v,n}(T+1)} |_{\tilde{p}_{v,n}(T+1), \tilde{\sigma}_{v,n}(T+1)} = \sigma_{v,n}(T+1) \left[ P_{n}^{\text{min}}(T+1) - \sum_{v=1}^{N_n(T+1)} p_{v,n}(T+1, \theta_{v,n}(T+1)|\Theta_n(T+1)) \right] = 0 \quad (D.2m)
\]

\[
\frac{dL_n}{d\mu_{v,n}^{\text{upp},1}(T)} |_{\tilde{p}_{v,n}(T)} = p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) - P_{v,n}^{\text{max}}(T) \quad \leq 0 \quad (D.2n)
\]

\[
\frac{dL_n}{d\mu_{v,n}^{\text{upp},1}(T+1)} |_{\tilde{p}_{v,n}(T+1)} = p_{v,n}(T+1, \theta_{v,n}(T+1)|\Theta_n(T+1)) - P_{v,n}^{\text{max}}(T+1) \quad \leq 0 \quad (D.2o)
\]

\[
\frac{dL_n}{d\mu_{v,n}^{\text{low},1}(T)} |_{\tilde{p}_{v,n}(T)} = p_{v,n}^{\text{min}}(T) - p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) \quad \leq 0 \quad (D.2p)
\]
\[
\frac{dL_n}{d\mu_{v,n}^{\text{low},2}(T+1)}|_{\hat{\varrho}_{v,n}(T+1)} = p_{v,n}^\text{min}(T+1) - p_{v,n}(T+1, \theta_{v,n}(T+1)|\Theta_n(T+1)) 
\]
\[
\leq 0 \quad (D.2q)
\]

\[
\frac{d\xi_n}{d\mu_{v,n}^\text{min}(T)}|_{\hat{\varrho}_{v,n}(T)} = \frac{1}{\zeta(t) C_{v,n} B} p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) - soc_{v,n}^\text{max} 
\]
\[
\leq 0 \quad (D.2r)
\]

\[
\frac{dL_n}{d\mu_{v,n}^{\text{up},2}(T+1)}|_{\hat{\varrho}_{v,n}(T+1)} = soc_{v,n}(t) + \sum_{t=T}^{T+1} \frac{1}{\zeta(t) C_{v,n} B} p_{v,n}(t, \theta_{v,n}(t)|\Theta_n(t)) - soc_{v,n}^\text{max} 
\]
\[
\leq 0 \quad (D.2s)
\]

\[
\frac{dL_n}{d\mu_{v,n}^{\text{min},2}(T)}|_{\hat{\varrho}_{v,n}(T)} = soc_{v,n}^\text{min} - soc_{v,n}(T) - \sum_{t=T}^{T+1} \frac{1}{\zeta(t) C_{v,n} B} p_{v,n}(t, \theta_{v,n}(t)|\Theta_n(t)) 
\]
\[
\leq 0 \quad (D.2t)
\]

\[
\frac{dL_n}{d\xi_{v,n}^{\text{low},2}(T+1)}|_{\hat{\varrho}_{v,n}(T+1)} = soc_{v,n}^\text{min} - soc_{v,n}(T) - \sum_{t=T}^{T+1} \frac{1}{\zeta(t) C_{v,n} B} p_{v,n}(t, \theta_{v,n}(t)|\Theta_n(t)) 
\]
\[
\leq 0 \quad (D.2u)
\]

\[
\frac{dL_n}{d\sigma_{v,n}^\text{up}(T)}|_{\hat{\varrho}_{v,n}(T)} = \sum_{v=1}^{N^V_n(T)} p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) - P_n^\text{max}(T) 
\]
\[
\leq 0 \quad (D.2v)
\]

\[
\frac{dL_n}{d\sigma_{v,n}^\text{low}(T+1)}|_{\hat{\varrho}_{v,n}(T+1)} = \sum_{v=1}^{N^V_n(T+1)} p_{v,n}(T+1, \theta_{v,n}(T+1)|\Theta_n(T+1)) - P_n^\text{max}(T+1) 
\]
\[
\leq 0 \quad (D.2w)
\]

\[
\frac{dL_n}{d\sigma_{v,n}^\text{min}(T)}|_{\hat{\varrho}_{v,n}(T)} = P_n^\text{min}(T) - \sum_{v=1}^{N^V_n(T)} p_{v,n}(T, \theta_{v,n}(T)|\Theta_n(T)) 
\]
\[
\leq 0 \quad (D.2x)
\]

\[
\frac{dL_n}{d\sigma_{v,n}^\text{low}(T+1)}|_{\hat{\varrho}_{v,n}(T+1)} = P_n^\text{min}(T+1) - \sum_{v=1}^{N^V_n(T+1)} p_{v,n}(T+1, \theta_{v,n}(T+1)|\Theta_n(T+1)) 
\]
\[
\leq 0 \quad (D.2y)
\]
\[ \mu_{v,n}^{\text{upp},1}(T) \geq 0 \quad (D.2z) \]
\[ \mu_{v,n}^{\text{low},1}(T) \geq 0 \quad (D.2aa) \]
\[ \mu_{v,n}^{\text{upp},1}(T+1) \geq 0 \quad (D.2ab) \]
\[ \mu_{v,n}^{\text{low},1}(T+1) \geq 0 \quad (D.2ac) \]
\[ \mu_{v,n}^{\text{upp},2}(T) \geq 0 \quad (D.2ad) \]
\[ \mu_{v,n}^{\text{low},2}(T) \geq 0 \quad (D.2ae) \]
\[ \mu_{v,n}^{\text{upp},2}(T+1) \geq 0 \quad (D.2af) \]
\[ \mu_{v,n}^{\text{low},2}(T+1) \geq 0 \quad (D.2ag) \]
\[ \sigma_{v,n}^{\text{upp}}(T) \geq 0 \quad (D.2ah) \]
\[ \sigma_{v,n}^{\text{low}}(T) \geq 0 \quad (D.2ai) \]
\[ \sigma_{v,n}^{\text{upp}}(T+1) \geq 0 \quad (D.2aj) \]
\[ \sigma_{v,n}^{\text{low}}(T+1) \geq 0 \quad (D.2ak) \]
Now, the control price signal of the problem follows (D.2a) and is derived similar to the single period problem. However, it should be noted that using this control price signal as an input variable for $\pi_n(T)$ in the single period problem formulation will give a different optimization result than attained by the MPC set up. This is because, in the single period solution, the influence of the future is neglected by neglecting the evolution of the marginal utility function and the Lagrangian multipliers. The latter are introduced by the constraints representing future time steps. Equation (D.2a) can be restructured into

$$\theta_{v,n}(T) \left[ \frac{\alpha_{v,n}(T)}{\varsigma(T)} - \frac{2\beta_{v,n}(T)}{\varsigma(T)} (soc_{v,n}(T) - soc_{v,n}^{\min} + \frac{p_{v,n}(T,\theta_{v,n}(T)|\Theta_{n}(T))}{\varsigma(T)c_{v,n}^{B}}) \right] =$$

$$\frac{\pi_n(T)}{\varsigma(T)} + \frac{\theta_{v,n}(T+1)\alpha_{v,n}(T+1)}{\varsigma(T+1)} - \frac{2\theta_{v,n}(T+1)\beta_{v,n}(T+1)}{\varsigma(T+1)} (soc_{v,n}(T + 1) - soc_{v,n}^{\min} + \frac{p_{v,n}(T+1,\theta_{v,n}(T+1)|\Theta_{n}(T+1))}{\varsigma(T+1)c_{v,n}^{B}})$$

$$+ \mu_{v,n}^{\text{upp},1}(T) - \mu_{v,n}^{\text{low},1}(T) + \mu_{v,n}^{\text{upp},1}(T + 1) - \mu_{v,n}^{\text{low},1}(T + 1) + \mu_{v,n}^{\text{upp},2}(T) - \mu_{v,n}^{\text{low},2}(T) + \mu_{v,n}^{\text{upp},2}(T + 1) - \mu_{v,n}^{\text{low},2}(T + 1)$$

$$+ \sigma_n^{\text{upp}}(T) - \sigma_n^{\text{low}}(T) + \sigma_n^{\text{upp}}(T + 1) - \sigma_n^{\text{low}}(T + 1)$$

$$\Leftrightarrow$$

$$\theta_{v,n}(T) \left[ \frac{\alpha_{v,n}(T)}{\varsigma(T)} - \frac{2\beta_{v,n}(T)}{\varsigma(T)} (soc_{v,n}(T) - soc_{v,n}^{\min} + \frac{p_{v,n}(T,\theta_{v,n}(T)|\Theta_{n}(T))}{\varsigma(T)c_{v,n}^{B}}) \right] + \mu_{v,n}^{\text{upp},1}(T) - \mu_{v,n}^{\text{low},1}(T) + \mu_{v,n}^{\text{upp},2}(T) - \mu_{v,n}^{\text{low},2}(T) =$$

$$\frac{\pi_n(T)}{\varsigma(T)} + \frac{\theta_{v,n}(T+1)\alpha_{v,n}(T+1)}{\varsigma(T+1)} - \frac{2\theta_{v,n}(T+1)\beta_{v,n}(T+1)}{\varsigma(T+1)} (soc_{v,n}(T + 1) - soc_{v,n}^{\min} + \frac{p_{v,n}(T+1,\theta_{v,n}(T+1)|\Theta_{n}(T+1))}{\varsigma(T+1)c_{v,n}^{B}})$$

$$+ \mu_{v,n}^{\text{upp},1}(T + 1) - \mu_{v,n}^{\text{low},1}(T + 1) + \mu_{v,n}^{\text{upp},2}(T + 1) - \mu_{v,n}^{\text{low},2}(T + 1) + \sigma_n^{\text{upp}}(T) - \sigma_n^{\text{low}}(T) + \sigma_n^{\text{upp}}(T + 1) - \sigma_n^{\text{low}}(T + 1)$$

(D.3)
The control price signal for the MPC setup can be defined as the minimum of all values of $\pi_n(T) + \varsigma(T)\Psi_{v,n}(T,T+1)$, which can be calculated through:

$$\min_{\forall v \in V_n(T)} \left( \theta_{v,n}(T) - 2\beta_{v,n}(T)(\Theta_n(T)) + \mu_{\text{upp},1}(T) - \mu_{\text{low},1}(T) + \mu_{\text{upp},2}(T) - \mu_{\text{low},2}(T) \right) =$$

$$= \left( \Theta_n(T) + \mu_{\text{upp},1}(T) - \mu_{\text{low},1}(T) + \mu_{\text{upp},2}(T) - \mu_{\text{low},2}(T) \right) \forall v \in V_n(T)$$

(D.4)
Appendix E

Voltage Stability Foundations

The derivation of a voltage stability margin is based on the Thevenin equivalent of a supply zone $z$ shown in Fig. E.1. The supply zone is assumed to comprise a partly radial, i.e., weakly meshed, distribution network connected to a tap changing transformer. The network loading includes the PEV load. Using two load cases, the second one with only 90% PEV load, allows to lump the network and model it by a Thevenin circuit whose loading includes also the PEV load. The loading of the Thevenin circuit is denoted $Z_L$. Finding a maximum value for $R_L$ allows to calculate the maximum load which can be imposed on the zone by PEVs. The variables in the following equations are found in Fig. E.1.

\begin{align*}
U_{th} &= U_L + IZ_{th}, \quad \text{(E.1)} \\
U_L &= IZ_L, \quad \text{(E.2)} \\
U_L^* &= I^*Z_L^*, \quad \text{(E.3)} \\
S_L &= U_L I_L^*, \quad \text{(E.4)}
\end{align*}

where one can write

\begin{align*}
I^2 &= \frac{P_L^2 + Q_L^2}{U_L^2}, \quad \text{(E.5)} \\
\Leftrightarrow I^2 &= \left( \frac{U_{th} - U_L}{Z_{th}} \right) \left( \frac{U_{th}^* - U_L^*}{Z_{th}^*} \right), \quad \text{(E.6)}
\end{align*}
Figure E.1: Thevenin equivalent of an electrical network. The Thevenin equivalent is used to determine the maximal total load of the underlying supply zone so that compliance with voltage stability limits is ensured.

and using (E.5), the last equation can be rearranged into

\[
\frac{P_L^2 + Q_L^2}{U_L^2} = \frac{U_{th}^2 - U_L^2}{Z_{th}} \left( \frac{U_{th}^* - U_L^*}{Z_{th}^*} \right), \quad (E.7)
\]

\[\Leftrightarrow \frac{P_L^2 + Q_L^2}{U_L^2} Z_{th}^2 = U_{th}^2 - U_{th}^* U_L - U_{th} U_L^* + U_L^2, \quad (E.8)\]

\[\Leftrightarrow \frac{P_L^2 + Q_L^2}{U_L^2} Z_{th}^2 = U_{th}^2 - U_{th}^* U_L + U_L^*(U_L - U_{th}), \quad (E.9)\]

\[\Leftrightarrow \frac{P_L^2 + Q_L^2}{U_L^2} Z_{th}^2 = U_{th}^2 - U_{th}^* U_L + \frac{S_L^*}{I}(U_L - U_{th}), \quad (E.10)\]

\[\Leftrightarrow \frac{P_L^2 + Q_L^2}{U_L^2} Z_{th}^2 = U_{th}^2 - U_{th}^* U_L + \frac{S_L^*}{I}(-Z_{th}I), \quad (E.11)\]

\[\Leftrightarrow \frac{P_L^2 + Q_L^2}{U_L^2} Z_{th}^2 = U_{th}^2 - U_{th}^* U_L + Z_{th} S_L^*. \quad (E.12)\]

Then using

\[I^* = \frac{U_{th}^* - U_L^*}{Z_{th}^*}, \quad (E.13)\]

\[\Leftrightarrow U_L I^* = \frac{U_{th}^* U_L - U_L^2}{Z_{th}^*}, \quad (E.14)\]

\[\Leftrightarrow U_L I^* Z_{th}^* + U_L^2 = U_{th}^* U_L. \quad (E.15)\]
and inserting it properly in (B.34) gives

$$\frac{P_L^2 + Q_L^2}{U_L^2} Z_{th}^2 = \frac{U_{th}^2}{U_L^2} - \left[ U_L I^* Z_{th}^* + U_L^2 \right] + Z_{th} S_{th}^* \quad , \quad (E.16)$$

$$\Leftrightarrow \frac{P_L^2 + Q_L^2}{U_L^2} Z_{th}^2 = \frac{U_{th}^2}{U_L^2} - \left[ S_L Z_{th}^* + U_L^2 \right] + Z_{th} S_{th}^* \quad , \quad (E.17)$$

which is equivalent to

$$\frac{P_L^2 + Q_L^2}{U_L^2} Z_{th}^2 = \frac{U_{th}^2}{U_L^2} \left[ (P_L + jQ_L) (R_{th} - jX_{th}) \right]$$

$$+ \left[ (P_L - jQ_L) (R_{th} + jX_{th}) \right] \quad , \quad (E.18)$$

and can be simplified to

$$\Leftrightarrow \frac{P_L^2 + Q_L^2}{U_L^2} Z_{th}^2 = U_{th}^2 - U_L^2 - 2P_L R_{th} - 2Q_L X_{th} \quad . \quad (E.19)$$

Then, (E.19) can be rearranged into

$$\Leftrightarrow (P_L^2 + Q_L^2) (R_{th}^2 j X_{th}^2) = \frac{U_{th}^2}{U_L^2} U_L^2 - U_L^4$$

$$- (2P_L R_{th} + 2Q_L X_{th}) U_L^2 \quad , \quad (E.20)$$

which gives

$$\Leftrightarrow U_L^4 + (2P_L R_{th} + 2Q_L X_{th} - U_{th}^2) U_L^2 + (P_L^2 + Q_L^2) (R_{th}^2 + X_{th}^2) = 0 \quad , \quad (E.21)$$

$$\Leftrightarrow U_L^4 + 2P_L R_{th} U_L^2 + 2Q_L X_{th} U_L^2 - U_{th}^2 U_L^2$$

$$+ P_L^2 (R_{th}^2 + X_{th}^2) + Q_L^2 (R_{th}^2 j X_{th}^2) = 0 \quad . \quad (E.22)$$

Finally, (E.22) can be rearranged after the active power of the load $P_L$ because it is assumed that PEV drawn only active power from the network. Proper rearrangement gives

$$P_L^2 (R_{th}^2 j X_{th}^2) + 2P_L R_{th} U_L^2 + U_L^4 - U_{th}^2 U_L^2$$

$$+ Q_L^2 (R_{th}^2 + X_{th}^2) + 2Q_L X_{th} U_L^2 = 0 \quad , \quad (E.23)$$

which can be solved for the active power as (E.23) is a quadratic equation. The solution for the active power which results in a specific load voltage $U_L$ is found by

$$\Rightarrow P_{L,1,2} = (A \pm \sqrt{A^2 - B^2 C})/B \quad , \quad (E.24)$$
Appendix E. Voltage Stability Foundations

with

\[
A = -2R_{th} U_L^2 , \\
B = 2(R_{th}^2 + X_{th}^2) , \\
C = (U_L^4 - U_{th}^2 U_L^2 + Q_L^2 (R_{th}^2 + X_{th}^2) + 2Q_L X_{th} U_L^2) .
\]
Appendix F

Design Parameters of the Vehicle Fleet

Table F.1: Design parameters for vehicles modeled in the fleet.

<table>
<thead>
<tr>
<th>Powertrain</th>
<th>Fuel Type</th>
<th>Power [kW]</th>
<th>Weight [kg]</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICE</td>
<td>Gasoline</td>
<td>&lt;50</td>
<td>&lt;900</td>
</tr>
<tr>
<td>P-HEV</td>
<td>Diesel</td>
<td>50-70</td>
<td>900-1100</td>
</tr>
<tr>
<td>PHEV</td>
<td>Natural Gas</td>
<td>70-90</td>
<td>1100-1300</td>
</tr>
<tr>
<td>BEV</td>
<td>Electricity</td>
<td>90-110</td>
<td>1300-1500</td>
</tr>
<tr>
<td>FCV</td>
<td>Hydrogen</td>
<td>110-140</td>
<td>1500-1700</td>
</tr>
<tr>
<td></td>
<td></td>
<td>140-170</td>
<td>1700-1900</td>
</tr>
<tr>
<td></td>
<td></td>
<td>170-200</td>
<td>1900-2100</td>
</tr>
<tr>
<td></td>
<td></td>
<td>&gt;200</td>
<td>2100-2300</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1300-2600</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>&gt;2600</td>
</tr>
</tbody>
</table>
Appendix G

Metropolitan Area Network Data

G.1 The 150 kV Network Topology

Figure G.1: 150 kV Metropolitan area electricity distribution network which supplies the underlying 11 kV and 22 kV network.
G.2 The 380 kV Network Topology

Figure G.2: 220 kV and 380 kV network supplying the metropolitan area distribution network through 4 large transformers. The 220 kV and 380 kV network is connected to the 150 kV intra urban area distribution network.
Appendix H

Additional Case Study Results

H.1 Impacts of uncontrolled PEV Charging in the Metropolitan Area of Zurich
Appendix H. Additional Case Study Results

Figure H.1: Line loading at the 11-22 kV network level in the city of Zurich at peak load, i.e., 18:15, for uncontrolled PEV charging; Scenario A, years 2020, 2035, 2050.

(a) Line loading on the 11-22 kV network level in the city of Zurich at 18:15, Scenario A: 2020.

(b) Line loading on the 11-22 kV network level in the city of Zurich at 18:15, Scenario A: 2035.

(c) Line loading on the 11-22 kV network level in the city of Zurich at 18:15, Scenario A: 2050.
H.1. Uncontrolled charging, Scenario A & C

(a) Line loading on the 150 kV network level in the city of Zurich at 18:15, Scenario A: 2020.

(b) Line loading on the 150 kV network level in the city of Zurich at 18:15, Scenario A: 2035.

(c) Line loading on the 150 kV network level in the city of Zurich at 18:15, Scenario A: 2050.

Figure H.2: Line loading at the 150 kV network level in the city of Zurich at peak load, i.e., 18:15, for uncontrolled PEV charging; Scenario A, years 2020, 2035, 2050.
Appendix H. Additional Case Study Results

Figure H.3: Loading of 380 kV transformers in the city of Zurich during peak load times, i.e., 18:15, for uncontrolled PEV charging in Scenario A, year 2020, 2035 and 2050.
H.1. Uncontrolled charging, Scenario A & C

Figure H.4: Line loading at the 11-22 kV network level in the city of Zurich during peak load times, i.e., 10:00, for uncontrolled PEV charging in Scenario C, year 2020, 2035 and 2050.
Figure H.5: Line loading at the 150 kV network level in the city of Zurich at peak load times, i.e., 10:00, for uncontrolled PEV charging; Scenario C, years 2020, 2035, 2050.
H.1. Uncontrolled charging, Scenario A & C

Figure H.6: Loading of 380 kV transformers in the city of Zurich at peak load times, i.e., 10:00, for uncontrolled PEV charging; Scenario C, years 2020, 2035, 2050.
H.2 Effects of controlled PEV Charging in the Metropolitan Area of Zurich
Figure H.7: Line loading at the 11-22 kV network level in the city of Zurich at peak load, i.e., 10:00, for controlled PEV charging; Scenario C, years 2020, 2035, 2050.
Appendix H. Additional Case Study Results

(a) Line loading on the 150 kV network level in the city of Zurich at 10:00, Scenario C: 2020.

(b) Line loading on the 150 kV network level in the city of Zurich at 10:00, Scenario C: 2035.

(c) Line loading on the 150 kV network level in the city of Zurich at 10:00, Scenario C: 2050.

Figure H.8: Line loading at the 150 kV network level in the city of Zurich at peak load, i.e., 10:00, for controlled PEV charging; Scenario C, years 2020, 2035, 2050.
(a) Load of the 150kV transformer substations in the city of Zurich at 10:00, Scenario C: 2020.

(b) Load of the 150kV transformer substations in the city of Zurich at 10:00, Scenario C: 2035.

(c) Load of the 150kV transformer substations in the city of Zurich at 10:00, Scenario C: 2050.

Figure H.9: Loading of 150 kV transformers in the city of Zurich at peak load, i.e., 10:00, for uncontrolled PEV charging; Scenario C, years 2020, 2035, 2050.
Appendix H. Additional Case Study Results

Figure H.10: Loading of 380 kV transformers in the city of Zurich at peak load, i.e., 10:00, for controlled PEV charging; Scenario C, year 2020, 2035, 2050.
Figure H.11: Asset loading in the city of Zurich on the 11 kV and the 22 kV voltage level at 10:00 for controlled PEV charging in Scenario C, year 2050.
Appendix I

Additional Case Study Results for a Worst Case Scenario

I.1 Impacts of Controlled PEV Charging in the Metropolitan Area of Zurich
(a) Line loading on the 11-22 kV network level in the city of Zurich at 10:00, Scenario C: 2050.

(b) Line loading on the 150 kV network level in the city of Zurich at 10:00, Scenario C: 2050.

Figure I.1: Line loading at the 11-22 kV and the 150 kV network level in the city of Zurich at peak load, i.e., 10:00, for controlled PEV charging; Scenario C, the year 2050.
I.1. Controlled Charging, Scenario C, Worst Case

Figure I.2: Transformer loading at the 150 kV and the 380 kV network level in the city of Zurich at peak load, i.e., 10.00, for controlled PEV charging; Scenario C, the year 2050.
Appendix J

Modeling the Heat Content of the CHP Heat Storage

\[ Q_{w,CHP} = m_{w,CHP}C_{heat}^{w,CHP}(T - T_{amb}) \]  

(J.1a)

\[ \dot{Q}_{w,CHP} = -\alpha_{w,CHP}A_{w,CHP}(T - T_{amb}) + \Delta P_{CHP} \]  

(J.1b)

\[ \dot{Q}_{w,CHP} = m_{w,CHP}C_{heat}^{w,CHP} \frac{\delta T}{\delta t} \]  

(J.1c)

\[ \delta T/\delta t = -\frac{1}{\tau_{CHP}}(T - T_{amb}) + \frac{1}{\tau_{CHP}A_{w,CHP}}\Delta P_{CHP} \]  

(J.1d)

\[ \delta T/\delta t = -\frac{1}{\tau_{CHP}}(T - T_{amb}) + \frac{1}{\tau_{CHP}A_{w,CHP}A_{w,CHP}}\Delta P_{CHP} \]  

(J.1e)

\[ \delta T/\delta t = -\frac{1}{\tau_{CHP}}(T - T_{amb}) + \frac{1}{\tau_{CHP}A_{w,CHP}}\Delta P_{CHP} \]  

(J.1f)

Substituting \( T_{amb} = T_{min} \) when setting the minimal temperature bound to the ambient temperature, using the substitution

\[ x = \frac{T - T_{min}}{T_{max} - T_{min}}, \]  

(J.2)

and differentiating \( T \) after the continuous time \( t \) as

\[ \frac{\delta T}{\delta t} = \frac{\delta T}{\delta x} \frac{\delta x}{\delta t}, \]  

(J.3)

using

\[ \frac{\delta T}{\delta x} = T_{max} - T_{min}, \]  

(J.4)

and reinserting the term for \( x \) gives

\[ \frac{\delta T}{\delta t} \frac{1}{T_{max} - T_{min}} = -\frac{x}{\tau_{CHP}} + \frac{\Delta P_{CHP}}{\tau_{CHP}A_{w,CHP}A_{w,CHP}(T_{max} - T_{min})}. \]  

(J.5)
Appendix J. Modeling the CHP Storage

This can be rewritten into

\[
\dot{x} = -\frac{1}{\tau_{\mathrm{CHP}}} x + \frac{1}{E_{\mathrm{max}}^{\mathrm{CHP}}} \Delta P_{\mathrm{CHP}}, \quad (J.6)
\]

using

\[
E_{\mathrm{max}}^{\mathrm{CHP}} = m_w^{\mathrm{CHP}} C_{w,\mathrm{CHP}}^{\text{heat}} (T_{\mathrm{max}}^{\mathrm{CHP}} - T_{\mathrm{min}}^{\mathrm{CHP}}), \quad (J.7)
\]

\[
\tau_{\mathrm{CHP}} = \frac{m_w^{\mathrm{CHP}} C_{w,\mathrm{CHP}}^{\text{heat}}}{A_w^{\mathrm{CHP}} \alpha_{w,\mathrm{CHP}}}, \quad (J.8)
\]

with

\[
A_w^{\mathrm{CHP}} = \pi r_w^{2}, \quad (J.9)
\]

and

\[
V_w^{\mathrm{CHP}} = \rho_w^{\mathrm{CHP}} m_w^{\mathrm{CHP}} = 4 \pi r_w^{3}. \quad (J.10)
\]

Table J.1 gives the design parameters of the CHP heat storage. It is used to store excessive heat or draw missing heat when the operation point of the CHP is altered for control purposes. Note that the relation between the height of the heat storage and the diameter is assumed to be $H/D = 2:1$.

Table J.1: Heat storage design parameters of the CHP.

<table>
<thead>
<tr>
<th>Variable description</th>
<th>Unit</th>
<th>Symbol</th>
<th>Value</th>
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</thead>
<tbody>
<tr>
<td>Density</td>
<td>[kg/m³]</td>
<td>$\rho_{w,\mathrm{CHP}}$</td>
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</tr>
<tr>
<td>Water mass</td>
<td>[kg]</td>
<td>$m_{w,\mathrm{CHP}}$</td>
<td>10’765’551</td>
</tr>
<tr>
<td>Average heat capacity</td>
<td>[J/kg K]</td>
<td>$C_{w,\mathrm{CHP}}$</td>
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</tr>
<tr>
<td>Radius</td>
<td>[m]</td>
<td>$r_{w,\mathrm{CHP}}$</td>
<td>9.58</td>
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<td>$T_{\mathrm{max}}^{w,\mathrm{CHP}}$</td>
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</tr>
<tr>
<td>Minimum temperature</td>
<td>[°C]</td>
<td>$T_{\mathrm{min}}^{w,\mathrm{CHP}}$</td>
<td>60</td>
</tr>
<tr>
<td>Average heat transfer coeff</td>
<td>[W/m²K]</td>
<td>$\alpha_{w,\mathrm{CHP}}$</td>
<td>10</td>
</tr>
<tr>
<td>Energy content</td>
<td>[MWh]</td>
<td>$E_{\mathrm{max}}^{\mathrm{CHP}}$</td>
<td>350</td>
</tr>
</tbody>
</table>
Appendix K

Deriving the Control Law for the MPC Scheme using the CHP Heat Storage

Equation (J.6) is of the form

\[ \dot{x} = Ax + Bu, \]  

(K.1)

which is the well known continuous time, linear, state space model where \( A \) and \( B \) denote matrices while \( x \) is the state vector of the system and \( u \) is the input vector to the system. Since the system at hand has only one item, namely the heat storage, the matrices are reduced to the values

\begin{align*}
A &= -\frac{1}{\tau_{\text{CHP}}} \\
B &= \frac{1}{E_{\text{max}}^{\text{CHP}}}.
\end{align*}

(K.2)

In order to integrate the relation given in (J.6) in a control problem formulation which utilizes a stepwise optimization, the continuous time, linear, state space model needs to transformed into a discrete time, linear, state space model. Such a model is formulated as

\[ x(k + 1) = A_d x(k) + B_d u(k), \]  

(K.3)

where \( k \) denotes the time step to which the continuous problem is discretized. The parameters for the system states and the input variables
are derived according to the matrix exponentials

\[
\mathbf{A}_d = \exp(\mathbf{A}\tau) ,
\]
\[
\mathbf{B}_d = \int_{\varphi=0}^{\tau} \exp(\mathbf{A}\varphi)d\varphi\mathbf{B} .
\]

For the system of the CHP heat storage, the matrix exponentials are easily calculated to be

\[
\mathbf{A}_d = \exp\left(-\frac{1}{\tau_{\text{CHP}}}\tau\right) ,
\]
and

\[
\mathbf{B}_d = \left( -\tau_{\text{CHP}}\exp\left(-\frac{1}{\tau_{\text{CHP}}}\tau\right) + \tau_{\text{CHP}} \right) \frac{1}{E_{\text{max}}^{\text{CHP}}} ,
\]
\[
\mathbf{B}_d = -\tau_{\text{CHP}} \frac{\exp\left(-\frac{1}{\tau_{\text{CHP}}}\tau\right)-1}{E_{\text{max}}^{\text{CHP}}} .
\]
<table>
<thead>
<tr>
<th>Year Range</th>
<th>Position/Program/Experience</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007 – 2012</td>
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<tr>
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</tbody>
</table>
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