Electric Vehicle Charging Coordination
Economics of Renewable Energy Integration

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Abstract

Electric vehicles (EVs) are a new type of flexible load in the power system. They offer the ability to adapt the battery recharging process to a given objective. Charging coordination of EVs can be performed with respect to technical, economic or renewable energy integration objectives. The technical objectives encompass peak load reduction and energy loss minimization, the economic coordination objectives comprise cost minimization and profit maximization problems. The integration of renewable energy sources can be addressed by EV demand shifting that aims to balance the production of intermittent generators against system load.

This thesis investigates the coordination potential of EV charging activity from two perspectives: the individual demand side and, complementary to this, the supply side incorporated by an EV fleet aggregator. The analysis of individual behavior focuses on price-based charging coordination in the presence of optimally reacting EV-owners. The evaluation shows that charging coordination can generate considerable savings and also increases the relative utilization of volatile energy sources. Allowing for resale of stored energy to the power grid can further increase savings, but is limited by battery wear conditions.

The examination of the supply side focuses on an EV aggregator aiming to maximize the utilization of his renewable energy generation capacities by employing the demand flexibility of the EV fleet accordingly. Since mobility requirements need to be fulfilled, conventional controllable generators serve as a back-up for EV supply in this case. The solutions of the mixed integer optimization problem show that EVs provide considerable flexibility potential which can be used to balance intermittent generation sources. Further results suggest that EVs can cover more than 60% of their charging demand by renewable energy sources in almost any scenario under investigation. The subsequent analysis which applies a price-signal reflecting the scarcity of renewable generation shows that static prices are prone to overcoordination and thus do not take advantage of existing EV demand flexibility.

This work contributes to the field of Smart Grid research by adding new insights regarding the value of charging control mechanisms that enhance the utilization of renewable energy by EVs and reduce individual charging costs.

Acknowledgements

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Chapter 1

Introduction

The German "*Energiewende*" is an ambitious and groundbreaking initiative to transform the current mainly fossil and nuclear fission based energy supply of one of the foremost industrialized countries in the world to a sustainable and predominantly renewable energy powered system. The *"Energiewende"* thus addresses many facets of energy, and in particular electricity supply and demand in order to achieve the target of 50% primary energy consumption reduction in 2050 as compared to the value of 2008. This target encompasses an increase of the share of renewable electricity to 80% of the yearly demand until 2050 (BMU, 2012b).

The goals of Germany are in tune with the intentions of the European Union to dramatically reduce its carbon footprint, according to the goals formulated in the Roadmap 2050. It states that greenhouse gas emissions are to be reduced by 80% until 2050 as compared to the year 1990. This goal also builds on a highly decarbonized power system with a high share of renewable energy (ECF, 2010).

In order to address these goals all sectors of energy supply and consumption must be examined with respect to their effectiveness, their carbon footprint, and in particular their short and long run costs to society. In the German context, the first steps of the transition were focused on the power system. Now other sectors such as transport are increasingly being considered. In the near future these yet still separated sectors will continue to build up interdependencies as Electric Vehicles (EVs) are increasingly established as an alternative for individual transportation. EVs are about three times more energy efficient[1] than conventional Internal Combustion Engine Vehicles (ICEVs), a circumstance that provides substantial energy saving and emission reduction potentials (Pollet

[1] Average tank to wheel efficiency of EVs 66.5%, ICEV 15.1-17.8%. Primary energy efficiency is dependent on EV power source.

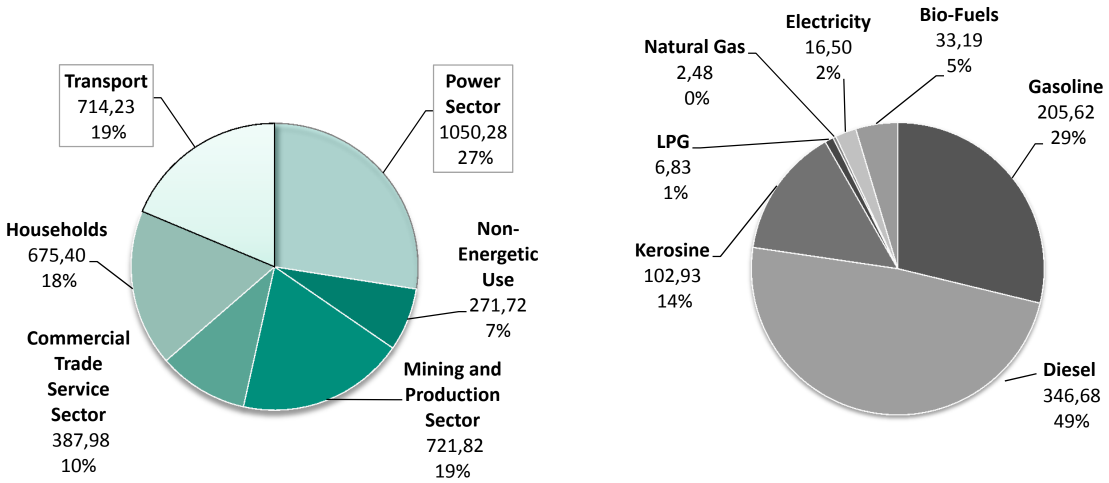


Figure 1.1: Primary energy consumption of Germany in TWh by sector (left) and by fuel in the transport sector (right) for the year 2012 (AGEB, 2013).

et al., 2012). This potential can only be unlocked if predominantly renewable energy sources are employed to charge the EVs. Another important aspect of EVs is that they effectively reduce the dependency on oil from politically unstable geographical regions and thus contribute to a higher energy supply security (Sovacool and Hirsh, 2008; Kintner-Meyer et al., 2007).

The convergence of the transport and power sector can substantially increase the energy efficiency of individual transport and reduce related carbon emissions. Transportation accounts for 19% of the primary energy consumption of Germany, whereas the power sector is responsible for the highest share with 27% or 1050 TWh in the year 2012 (cf. Figure 1.1). Energy demand in the transport domain is covered to 93% by fossil fuels or their derivatives. At the end of 2012 more than 43 million light vehicles were registered in Germany, with about 30 million gasoline and 12 million diesel fueled vehicles (KBA, 2013). Electric and hybrid vehicles have seen high growth rates of more than 30%-56% per year but still constitute only a small share of the vehicle market. Nevertheless, the ever increasing variety of models and lower end-consumer prices is starting to positively affect the demand for EVs. The potential energy savings of a fully electrified light vehicle fleet in Germany would amount to more than 200 TWh. The effects of a wide-scale EV adoption are thus two fold: firstly, a higher primary energy efficiency is achieved and secondly, emissions are further reduced if only renewable energy sources are used to supply the vehicles.

1.1 Electric Vehicles for Demand Response in Smart Power Systems and Markets

During the last decade Germany has witnessed an unprecedented increase in renewable, and in particular volatile, generation capacity. Based on the security provided by the Renewable Energy Act (EEG), which guarantees a fixed feed-in tariff differentiated by generator type and its specific capital costs, the installed capacity of wind-power and solar photovoltaics (PV) surpassed 29 GW for these sources in 2012 (cf. Figure 2.1), BMU (2012a). In total more than 65 GW of renewable capacity are online as of 2012, at a total installed generation capacity of 172 GW in Germany (BNetzA, 2012). The formerly centralized power system thus becomes more decentralized and requires an increasingly more flexible demand side and more flexible generators to enable a safe and stable operation. Since a main part of the renewable supply is intermittent and uncontrollable in its generation output, the demand side, and in particular EVs, need to coordinate their charging activities in order to realize the full efficiency and emission reduction potential.

The Smart Grid paradigm is one building block to enable the integration of numerous decentralized generation and demand side resources. It enables an efficient communication and control in the increasingly decentralized structures. The Smart Grid can be understood as a combination of enabling ICT technologies (hardware, software, or practices) that jointly make the power delivery infrastructure - in particular the grid - more reliable, versatile, secure and more accommodating for the integration of distributed and intermittent resources. This will make the grid ultimately more useful to consumers (Sioshansi, 2011).

The Smart Grid thus has the potential to change the power system structure in order to address one of the main demand side flaws of power markets: the lack of real time metering and billing and related to this, the information and active integration of the demand side in the price determination of power supply for a given time interval (Stoft, 2002). In a decentralized system power flows become bidirectional, which also requires communication between the distributed resources to safely operate the grid. An active demand side, and in particular demand response is crucial for an economically efficient and technically secure operation of a power system with a high share of variable generation sources. The value of demand response is higher in rather inflexible conventional generation structures as they are still prevalent in Germany (Strbac, 2008).

Flexible loads such as EVs offer the potential to participate as active demand resources in the balancing of the power grid, be it on a local or global level. EVs are rather large loads, since they are comparable to the load of an average German household with respect to their yearly energy demand[2]. EVs are already equipped with charging controllers that can implement different charging strategies given the available infrastructure. The possibilities of EV charging coordination will thus further be investigated in this thesis.

1.2 Research Questions

Active demand side integration can be implemented in different ways. At the center of this work are price based demand response programs and the assessment of EV demand side flexibility for the integration of fluctuating renewable energy generation sources in a smart grid environment.

1.2.1 Individual Economic Assessment of EV Charging Strategies

At the core of price based demand response programs are variable price incentives (Albadi and Elsaadany, 2008), implemented by e.g. a temporally varying energy price. This enables EV-owners to decide to what extent they are willing to adapt their demand according to their preferences. Following the basic spot pricing concept of Caramanis et al. (1982), a variable pricing scheme based on empirical price data of the German wholesale market is employed as the economic basis of the following analysis. Given different goals or system operation settings the variable price can function as a scarcity signal to adequately represent the availability of certain resources such as renewable power or distribution grid capacity (Flath et al., 2013).

Existing analyses dedicated to the assessment of the economic viability of different price based charging strategies for EVs either focus on the provision of ancillary services and in particular regulation services (Andersson et al., 2010; Kempton and Tomić, 2005a; Sortomme and El-Sharkawi, 2011) or on the system wide impact of large numbers of EVs with respect to the market outcome (Sioshansi, 2012; Sioshansi and Miller, 2011; Goebel, 2013). The provision of regulation by EVs in a vehicle-to-grid (V2G) operation mode is analyzed and found

[2]Standard three person household yearly consumption in Germany: 3400 kWh. This corresponds to a yearly driving distance of 17,600 km at 0.18 kWh/km and 93% charging efficiency (BDEW, 2012).

to be potentially profitable (Andersson et al., 2010; Kempton and Tomić, 2005a). V2G though requires a reliable availability of EVs for power grid purposes and needs to be performed under considerations of battery degradation parameters (Peterson et al., 2010). Further technical analyses which focus on distribution grid loss minimization and peak load reduction do only consider direct control schemes or simplistic time-of-use (TOU) tariffs without performing an individual economic evaluation (Acha et al., 2010; Lopes et al., 2010).

In this complex environment of technical and economic interdependencies, this work contributes by providing a predominantly individual economic evaluation of different objectives for EV charging coordination. Given empirical data for prices and the modeling of driving patterns and economically rational EV-owners the following first research question (RQ) is addressed:

RQ 1 - Cost of Individual EV Charging: *What are the individual electricity costs of EVs following an uncoordinated, economically optimized, system load minimal or wind-energy share maximizing charging strategy?*

The investigation of this and related questions is performed in Section 4.2 by implementing and solving linear optimization models that minimize the electricity costs incurred by an individual EV, given that the mobility requirements are always fulfilled. Further analyses consider a more sophisticated representation of battery degradation costs in a comparable setting as above. In addition the feed-in of energy into the power grid (i.e. V2G) is also considered and evaluated with respect to its individual economic viability. The consequential research question is thus:

RQ 2 - Economic Evaluation under Consideration of Storage Costs: *What are the individual costs, including battery degradation, of charging and discharging electric vehicles employing a cost minimizing charging strategy while still fulfilling the given mobility profile?*

This analysis is described in detail in Section 4.3 and implements a quadratic linear optimization objective function which is minimizing the resulting costs by choosing lower price intervals for charging and by adjusting the power rate at which charging occurs such that the overall individual costs including the battery degradation costs are adequately accounted for. The constraints that are considered include, as before, the fulfillment of the individual driving profile of every EV in the optimization period, as well as the adherence to the EV and charging infrastructure specifications. Also the economic assessment is improved with respect to the German power market regulation framework and thus allows for a more realistic evaluation of the economic viability of wholesale energy market based V2G charging strategies.

1.2.2 Renewable Energy Integration Potential of EV Fleets

Following the individual economic perspective, the demand flexibility potentials of EV fleets and their capability to directly utilize fluctuating renewable power sources need to be assessed. EVs charged with renewable power reduce their lifetime emissions by at least 80% as compared to conventional vehicles (Helms et al., 2010)[3].

Since the demand of one EV is comparably small even to most decentral renewable generation sources, the capacity of several EVs needs to be bundled by a coordination instance to make it accessible to the power system or the respective market. For this task the role of the EV aggregator is introduced in literature (Kempton and Letendre, 1997; Bessa and Matos, 2012). Most analyses focus on the reduction of imbalances caused by volatile renewable generators through EVs (Galus and Andersson, 2011; Druitt and Frueh, 2012; Goeransson et al., 2010) and the potential of the vehicles to reduce emissions in large power systems (Denholm and Short, 2006). In contrast to this there is little work that directly evaluates the flexibility potential of EV demand to respond to intermittent generation patterns. In addition EV mobility patterns are mostly approximated and not based on empirical input data as in the work at hand.

Given the context of an EV aggregator fleet and a fixed intermittent generation capacity over the analysis time frame, the following research question is addressed:

RQ 3 - Scheduling for Renewable Energy Utilization: *Which share of renewable energy can be directly utilized by a fleet of EVs being scheduled according to different renewable generation patterns in comparison to an uncoordinated charging strategy?*

This question is analyzed in Section 5.2 by using a supply side centered mixed integer optimization problem. The objective function of the EV aggregator is to minimize the dispatch of a conventional controllable generator, given an in-

[3]Based on a life-cycle analysis including the emissions for the manufacturing of the vehicles. Operative emissions for wind-power are 24 g CO2 / kWh as compared to coal-power with 750 g CO2 / kWh (UBA, 2011; Burkhardt et al., 2007).

termittent generation profile of wind and/or solar source for the optimization period of one week. Since the intermittent supply is inherently uncertain over longer periods of time, the optimization is also performed under similar assumptions for a shorter optimization horizon of one day, but still for the consecutive period of 51 weeks of the year.

The analysis establishes a benchmark for the ability of EV fleets to adapt their demand to a volatile, but known, generation source while fulfilling mobility requirements. This assumes hierarchical direct load control of the participating EVs. Since not all EV-owners are likely to let the utility company control their individual charging process, price based incentives as addressed in the previous section are also evaluated as a means of charging coordination for the aggregator following a decentral decision making paradigm. The corresponding research question can thus be formulated as follows:

RQ 4 - Price Based Renewable Energy Utilization: *Which percentage of renewable energy can be utilized by a fleet of EVs if charging is coordinated via a price signal mapping the scarcity of these intermittent sources?*

This question and an additional economic evaluation based on the wholesale energy market prices of the resulting charging actions are addressed in Section 5.3. The approach employs an individual linear optimization model that, given a variable price from the aggregator, minimizes the electricity costs of the EV-owner. This part of the model corresponds with the approach in Section 4.2. In the other part of the model the variable price calculation of the aggregator based on the availability of renewable power, the availability of the vehicles and the conventional back-up generator is performed. This conventional resource ensures that all mobility requirements are fulfilled appropriately.

Chapter 5 thus provides insights on the ability of EVs to utilize renewable power sources, possible charging coordination mechanisms and their incentives, and an economic evaluation based on empirical price data of the German wholesale energy market.

1.3 Structure of the Thesis

The thesis is structured as follows (cf. Figure 1.2): Chapter 2 lays the foundations for a comprehensive understanding of the power system structure, the current and future developments with respect to the Smart Grid and demand response

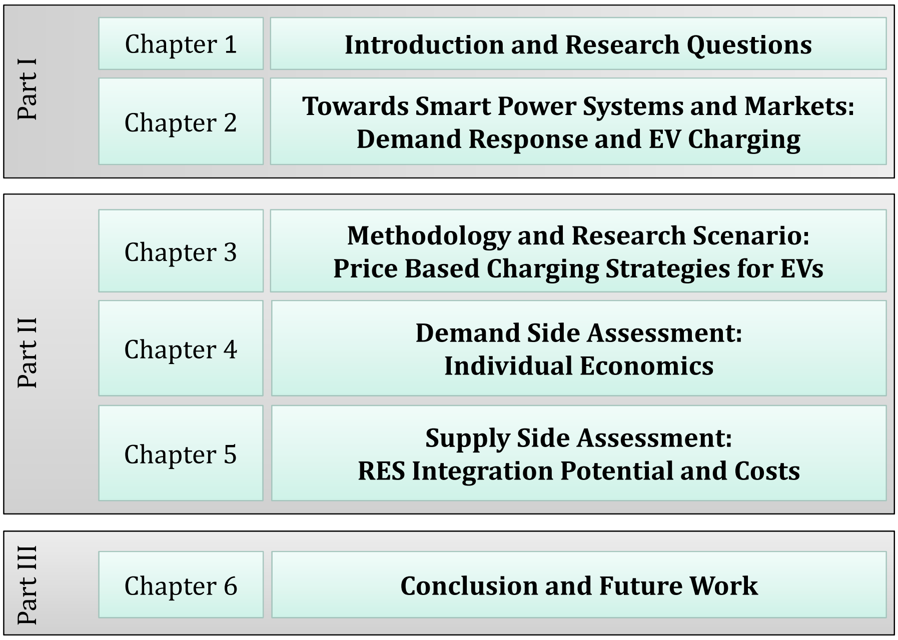


Figure 1.2: Overview of the thesis structure.

in the particular case of EVs. It also addresses previous work from the context of EV charging coordination and its technical, renewable energy integration and economic optimization centered objectives.

Chapter 3 characterizes the methodological background and the input data that is employed for the simulation based analyses. Chapter 4 then provides a demand side perspective and thus individual evaluation models and results with a predominately economic focus, while Chapter 5 performs the potential analysis with respect to the integration ability of renewable power by EVs and an economic evaluation of resulting charging actions. Chapter 6 summarizes the findings and provides conclusions that result from the evaluation. Finally limitations of the analysis and future work opportunities are addressed.

Chapter 2

Towards Smart Power Systems and Markets: Foundations

2.1 Introduction

The goal of this chapter is to capture the main context of the research questions that are going to be addressed in Sections 4 and 5. Electric Vehicles are an increasingly important part of the current and future power markets and systems. In order to give a comprehensive description of their role, this chapter focuses on the general development of power markets in Europe and especially Germany, as well as the definition, the development and deployment of the Smart Grid and its infrastructure. This will enable a more active demand response, a crucial concept that is necessary to integrate the intermittent power sources into the system, and a field in which EVs can subsequently play an important role.

2.2 Development of the Power System

Developments like the Smart Grid or Demand Response are a special and more recent part of a long development of the power system since its large scale rollout starting in the end of the 19th century. Therefore this section will capture some of the most relevant steps of this important evolution.

After groundbreaking electro-physical discoveries in the beginning and the mid 18th century (e.g. by Alessandro Volta, Michael Farraday and James Clark Maxwell), continuous development made electric power a new source of energy in the urban centers of Europe and primarily the east coast of the United States by the 1880s (Schwab, 2009). The prevailing technology at this time was Thomas Edisons Direct Current (DC) System. Lighting and increasingly electric engines were the main loads that had to be served by the DC power system. The electric light system was competing with the gas powered infrastructure and could provide better lighting while being less expensive and potentially less harmful when malfunctions occurred. The convenience of turning electric appliances simply on and off, and the less infrastructure demanding installation as compared to other sources of energy, made, and still make electricity one of the most important sources of energy in daily applications. This fact is due to the physical properties of electricity and its high amount of "*Exergy*", i.e. the high amount of usable energy for the foreseen application.

The DC power system was by design and mostly because of its physical constraints a local, or distributed system. Power was generated near to the load that needed it, e.g. in factories for the manufacturing processes, or near or in the middle of communities that constituted the consumers. This was mainly due to the fact, that with increasing distance from the generator, the losses in a DC system increase. Due to the constraints of Ohms Law the resistance of a conducting material will increase proportional to its length, given a fixed diameter (Tipler and Mosca, 2008). So comparably short distances (i.e. less then 10 km) to the sources were necessary to still deliver a significant part of the generated electricity to the designated loads.

In contrast to this the AC or alternating current system significantly advanced by Nikola Tesla and promoted by George Westinghouse had different properties. One of the most relevant differences to the DC system is the fact that not all system components have to operate at the same voltage level. The voltage level of 110 V which was standard in the United States at the time, would be applied to all connected consumers, so appliances needed to be designed to operate at this level. On the other side, this fact constrained the possibility to use higher voltages for transmission of electric distances. The physical properties of AC allowed to uncouple the transmission and distribution of electricity because transmission could be done at higher voltages but lower currents which in turn reduced the losses considerably. Supported by invention of the AC motor and improved transformer design by Tesla, the AC system started to prevail against the DC system, as higher powered stations and higher voltages were installed to cope with the growing demand. AC bases systems finally became the world standard being implemented in different fashions but mainly with a frequency of either 50 or 60 Hz and a distribution system voltage of 220-240 or 110-120 volt (El-Hawary, 2008).

2.2.1 Power System Economics

As the power systems covered more and more load the individual power stations were increasingly connected to each other by high voltage transmission lines. This increased the quality and reliability of service and stepwise lead to the highly interconnected systems that are in place today. The electricity grid is a natural monopoly, as due to the subadditivity of the utilities cost-functions, it does not make economic sense to install more than one connection to the same load if its requirements are physically met (Erdmann and Zweifel, 2007). Generation in turn can be allocated in a competitive market if transparent and non-discriminatory access to the transmission grid is granted (Stoft, 2002). But the prevailing solution in the starting times of the power infrastructure were integrated utility companies, operating both generation and distribution of electric energy. In some European countries, including Germany, integrated utility companies were mostly owned by a local or federal governments, as electricity was and still is perceived as an important strategic asset for the economic development of a country (Krisp, 2007). In North America a private sector owned integrated utility model was adopted including regulation by federal institutions like the Federal Energy Regulatory Commission (FERC) (El-Hawary, 2008). This operational model of the power system was profoundly altered by the liberalization initiatives carried throughout the 1980s and 1990s to in North America and Europe.

The liberalization of the power sector followed a general trend in which state owned or highly regulated natural monopoly industries were stepwise deregulated or restructured and subsequently privatized as for example, air lines, mail and rail systems and more similar in structure to the power sector, telecommunications. The general goal of the liberalization process was to

> "*..create new institutional arrangements for the electricity sector that provide long-term benefits to society and to ensure that an appropriate share of these benefits are conveyed to consumers through prices that reflect the efficient economic cost of supplying electricity and service quality attributes that reflect consumer valuations.*"(Joskow, 2008).

The means by which this was to be, or should be achieved included the privatization of state-owned monopolies to create hard budget constraints and incentives for performance improvements, vertical separation of potentially competitive segments (like generation, marketing and retail supply) from segments that would be continued to be regulated (transmission, distribution, system operation). In addition a horizontal restructuring of the generation segment was needed in order to create an adequate number of competing generators thus mitigating market power of single generation firms. The creation of an independent institution to run a wholesale spot energy and operating reserve market for real time balancing of demand and supply and to organize system management and operation, commonly referred to as the Independent System Operator (ISO) was also necessary. Many countries, and several states in the U.S. adopted the major institutions mentioned before, but there are still considerable differences between the "textbook" model of market liberalization and restructuring and the actual implementation in place (Joskow, 2008).

In Europe and especially in Germany market liberalization was initiated first in the retail segment. This opened up the market for increased retail competition between suppliers, but initially left the conventional regional monopolistic structure of the generation and transmission sector untouched. This changed from 2005 on, as the required legal and later ownership unbundling of vertically integrated utilities was gradually realized, following the requirements of EU-regulation and the steps mentioned above.

Besides market restructuring, the political initiative to create a more sustainable power system and technological improvements by introducing and supporting renewable generation technologies since the early 1990s continued to alter the overall system properties. Renewable generation sources are predominantly distributed resources that mostly have an intermittent generation pattern which cannot be controlled in its general output level, i.e. wind and solar generation. After the beginning of market liberalization in Germany in 1996 through 1998, the government increasingly supported the development of renewable energy by passing legislation which guaranteed new renewable generation a fixed compensation per kWh produced, a feed in tariff that would cover for the investment and operation costs for each generator and some surplus. This law, the Renewable Energy Act ("Erneuerbare Energien Gesetz", EEG) initiated an unprecedented growth of distributed and renewable generation capacity in Germany over the last decade, cf. Figure 2.1 (BMU, 2012a).

2.2.2 Towards the Green Power System

The installation of new renewable generation capacity was at first dominated by wind-power. But as most of the more profitable sites in northern and eastern Germany were allocated, or not included for development due to political

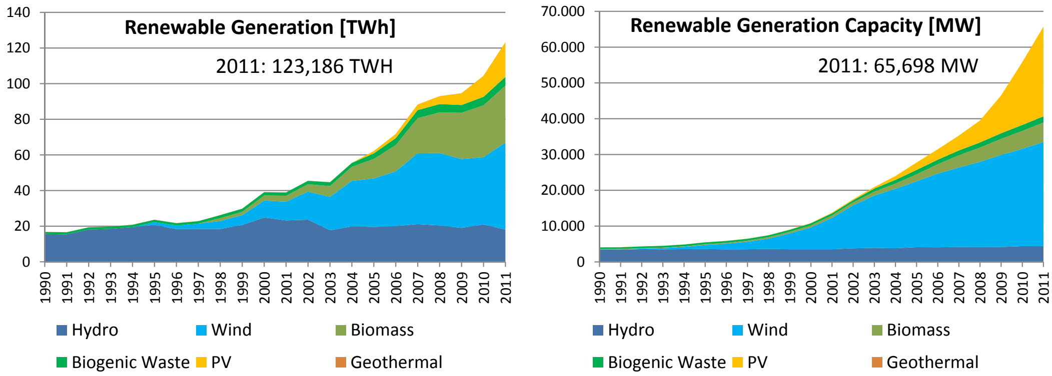


Figure 2.1: Development of renewable electricity generation and capacity in Germany since 1990, BMU (2012a).

reasons, Photovoltaics (PV) increasingly contributed to the new capacity as installation prices dropped from 2006 on to the present day in 2013. Biomass and especially Biogas contributed increasingly, reaching a level of 5.4 GW of installed capacity at the end of 2011 (BMU, 2011). Wind-power topped 29 GW and PV more than 25 GW in 2011 while installation rates for 2012 kept growing even though the feed in tariff for PV was substantially lowered to slow down installations for reasons of cost control and grid stability, resulting in a installed PV capacity of over 29.7 GW in mid-2012 (BSW, 2012). Through this increasing dynamic in the installation of renewable generation sources, Germany was able to cover more than 20 % of its gross yearly power consumption by renewable sources at the end of 2011 (BMU, 2012a). The German power sector is thus being reshaped continuously by three major driving forces: the market liberalization process which now focuses on a stronger connection and synchronization with the surrounding countries, the dynamics of the renewable generation development and by the stepwise nuclear phase-out until 2022.

These developments put a high pressure of the conventional power system architecture. This architecture was defined by the needs of centralized integrated utilities formed by the developments in the beginnings of the power system as described above. The main structure relies on three general voltage levels, a high voltage (HV) transmission and subtransmission network (including voltages between 35 - 110 kV, and 230 - 380 kV for Extra-HV), a medium voltage distribution network (voltages of 1kV - 30 kV) for regional and shorter interregional connection, and the low voltage network with 0.22-0.38 kV for the connection of end-customers (Erdmann and Zweifel, 2007; El-Hawary, 2008).

The transmission and in particular the distribution networks were designed

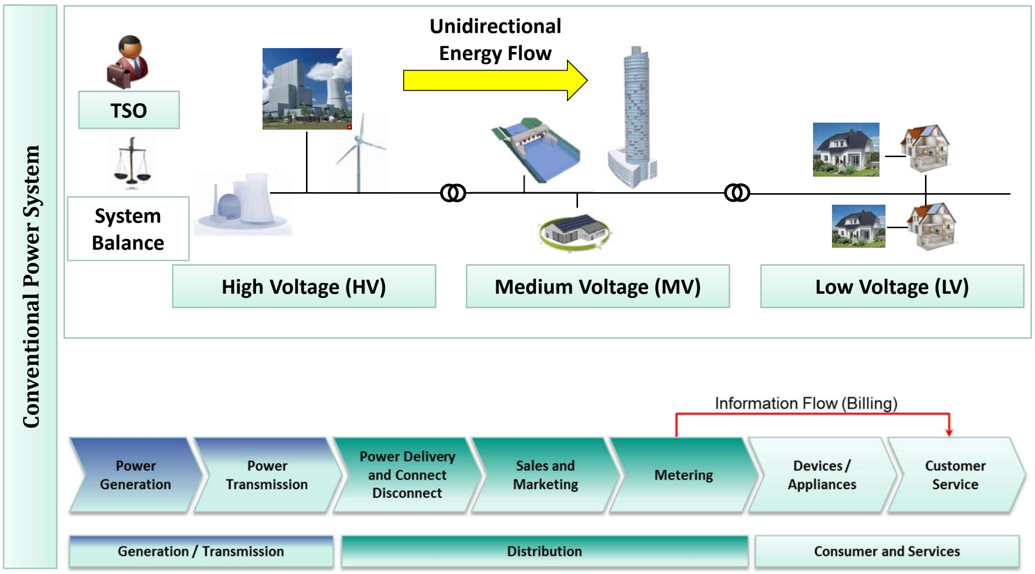


Figure 2.2: Structure and value chain of the conventional power system. (Own illustration and according to Valocchi et al. (2007))

to deliver the energy from the centralized power generation unit to the more or less distant customers on the medium and low voltage network. This included only a unidirectional flow of energy from the source to the consumer, cf. Figure 2.2. In this system distribution level companies would serve their customers and also communicate a forecast of the expected load based on historic data and weather conditions of their control region to the respective transmission system operator (TSO) or independent system operator in the North American power system. The TSO/ISO would then determine for at least one day ahead for each 5-15 minute time interval of the next day, which load was expected and would dispatch the available generation accordingly. This generation used to be, and still is in large parts constituted by thermal power plants that can be controlled in their output in order to follow the load in every time step. The economic dispatch will be further addressed in section 2.5. Also the TSO or ISO is operating the system and purchases ancillary services in order to guarantee a stable system frequency of 50 Hertz (Hz) in Europe, or 60 Hz in the U.S.. This is achieved by balancing system load and generation in every instant during operation.

The general value creation chain and service delivery was organized according to this centralized energy delivery paradigm. The vertically integrated utilities often combined several or all of these steps in their company, from generation to transmission and distribution as well as sales, marketing and metering of end-customers. In this architecture the customer was mainly passive and not metered on a real time basis. As there was only a unidirectional power flow, there also was only a mostly unidirectional information flow, from the utility to the consumer, in general only for administration or billing purposes (Valocchi et al., 2007). The mentioned drivers are increasingly altering the requirements to the power system, which with a growing share of intermittent generation, needs do become more flexible in balancing load and generation as it is currently capable of when relying on the conventional system structure. Balancing requirements are mostly met by flexible generation units like combined cycle gas turbines (CCGT) or pumped hydro generation that can respond with high power change gradients to the requirements of the grid. These resources though are limited in their availability, be they constrained by the geographic properties of a country or the costs for keeping power plants on stand-by for renewable generation drop-outs or sudden load changes that they have to balance. Therefore, with increasing intermittent resources on the grid, a more flexible demand side is technologically necessary and also economically required, (Stoft, 2002; Ramchurn et al., 2012).

The development of the internet and its tremendous impact on nearly all sectors of the economy and society also enables a different way to operate and coordinate the power system. The increasingly distributed structure of generation and incrementally added flexible demand resources need to be coordinated to respond to fluctuations in the power grid. This requires an additional layer of ICT infrastructure for communication between these resources and the TSO / ISOs and with each other. Enabling communication and coordination between distributed generation and demand resources and the conventional actors in the power system can be facilitated by the infrastructure and the concept of the "*Smart Grid*", which will be explained in the next section.

2.3 The Smart Grid Concept

The term "Smart Grid" is not consistently defined in the same way in Europe or in the United States. Nevertheless there is a significant overlap of what this concept means to both regions. In Europe the Smart Grid and the according initiative envision a electricity network that must be (European Commission, 2006): *Flexible* to fulfill customers needs, whilst responding to the challenges of a restructuring and more decentralized power sector. Also it has to be *accessible*, meaning that it grants connections to all network users, in particular for renewable and high efficiency local generation with low carbon emissions. The next core characteristic is *reliability*, which assures security and quality of supply, consistent with the demands of the digital age with resilience to hazards and uncertainties. The last feature is an *economically efficient* network that can provide value through innovation, efficient energy management and competitive markets (European Commission, 2006).

In the U.S. the Smart Grid is perceived e.g. by the Department of Energy as:

> *A fully automated power delivery network that monitors and controls every customer and node, ensuring a two-way flow of electricity and information between the power plant and the appliance, and all points in between. Its distributed intelligence, coupled with broadband communications and automated control systems, enables real-time market transactions and seamless interfaces among people, buildings, industrial plants, generation facilities, and the electric network.* (Ramchurn et al., 2012)

In Germany, the definition of what the Smart Grid Concept encompasses are close to the European perspective, in particular it is perceived as a system that includes and links intelligent generation devices, storage appliances and network equipment by means of ICT. Its objective is a transparent and cost-efficient, as well as secure and robust system operation and sustainable supply of electric energy (DKE, 2010).

The Smart Grid can thus be seen as a combination of enabling technologies, hardware, software, or practices, that collectively makes the power sectors electricity delivery infrastructure - the grid - more reliable, versatile, secure, more accommodating and integrating for distributed and intermittent resources and ultimately more useful to consumers (Sioshansi, 2011).

The focus is to some extent different for the U.S. and Europe, while the U.S. has a stronger focus in enhancing, securing and renewing its power delivery infrastructure and a more active demand side, in Europe the focus is more on distribution level automation and integration of renewable energy and distributed resources (Coll-Mayor et al., 2007). A more active demand side is pursued in both concepts, as it is necessary for system stability and a more efficient market operation. Also both concepts have a strong focus on the technology and its implementation,(cf. Figure 2.3 for the ETP vision).

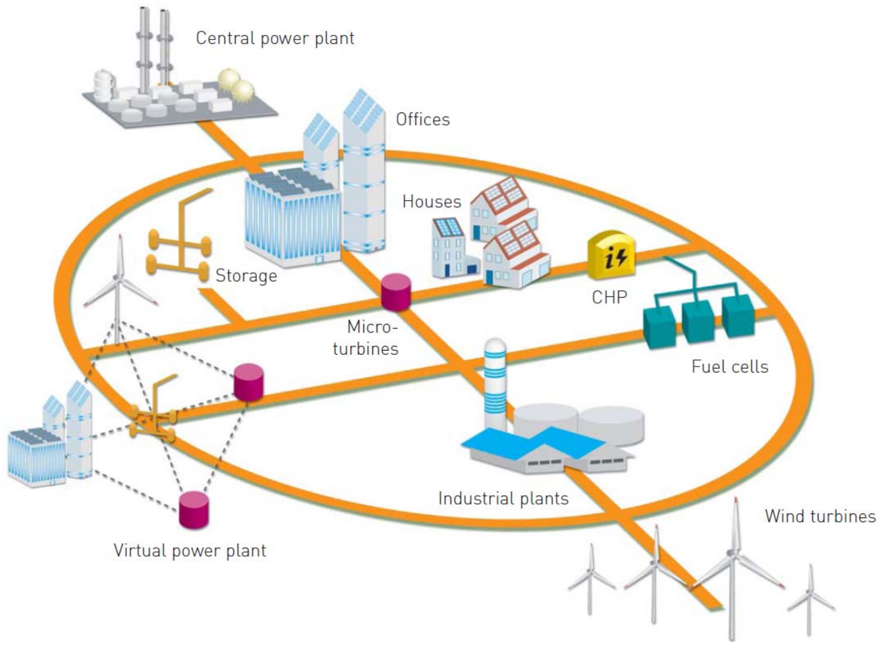


Figure 2.3: The future network structure as defined by the European Technology Platform SmartGrids, with a focus on virtual power plants and distributed resources (European Commission, 2006).

2.3.1 Benefits and Components of the Smart Grid

Following the different definitions the proposed benefits of the Smart Grid concept are therefore: A higher *reliability* of the system, a higher *demand side flexibility* and participation as well as the *integration of distributed and renewable* resources. Reliability can be increased by installation of distribution level automation and monitoring technologies, which enable to capture the system state already in local and regional settings and allow the Distribution System Operator (DSO) to identify and address impending outages earlier than before and quickly isolate fault areas. Also local demand side management can be employed to support system stability by balancing local intermittent supply. The ICT infrastructure enables an information flow that was not existent before the introduction of the Smart Grid concept. A self healing grid that recognizes faults, isolates and possibly corrects them, can also be supported by this infrastructure (Ramchurn et al., 2012).

Demand side management encompasses any coordinated actions to reduce and shift loads in a systematic way that the power system can be operated more stable and with less excess or peak capacity, Strbac (2008). This concept has so far mostly been applied to rather large consumers in the past, like steel mills or similar large size industrial customers. The Smart Grid lowers the transaction cost to address the large potential of shiftable load in the commercial and residential sector. A more flexible demand side enables local balancing of intermittent supply, but can also increase overall system stability as now not only generation levels can and need to be adjusted, but also load can be rescheduled to other times in order to operate the system in a safe and possibly less resource intensive way. In economic terms this would also enable a more efficient electricity market, which presently has only a low or nearly zero elasticity on the demand side. Thus the Smart Grid could address one of the general flaws of electricity markets, the lack of real time metering and billing of demand (Stoft, 2002). The first steps to the roll out of this technology are made in the residential sector in different countries like e.g. Sweden and Italy that already replaced the majority of residential metering systems by smart meters. Smart meters at the residential level and substation automation equipment are the main technical components of the Smart Grid in the distribution system.

These new metering systems allow every customer to monitor his own electricity consumption in real time and thus facilitate a response to changing system and market conditions by enabling more informed choices about energy use in general. In addition they can transmit the metering values in short time intervals to the utility company or directly to the DSO. Although communication infrastructure like the internet is now being taken for granted, smart meters can be also connected by other means (e.g. PLC, GSM) to the responsible actor, thus allowing for a more robust operation scheme. This again highlights the need for the deployment of standards for power driven communication applications, like IEC-62051-54/58-59 for metering data, or IEC-61851 for EV-communication (DKE, 2010). The vast amounts of metering data must be processed for operation and are also the basis for the financial settlement between the participating parties.

But the information of these sensor and actor systems needs to be processed and analyzed in a timely manner in order to allow for the mentioned system stability benefits to emerge. New platforms for energy consumption monitoring and management are thus required which can be provided and operated by new roles in the energy market (DKE, 2010; Ipakchi and Albuyeh, 2009).

A highly intermittent power supply can also be facilitated by the means of Smart Grid technology, as not only monitoring but the operational integration of intermittent supply can be supported. This could be done by clustering different intermittent supply sources and storage devices to virtual power plants (VPP) which can offer their electricity output in a more predictable fashion and

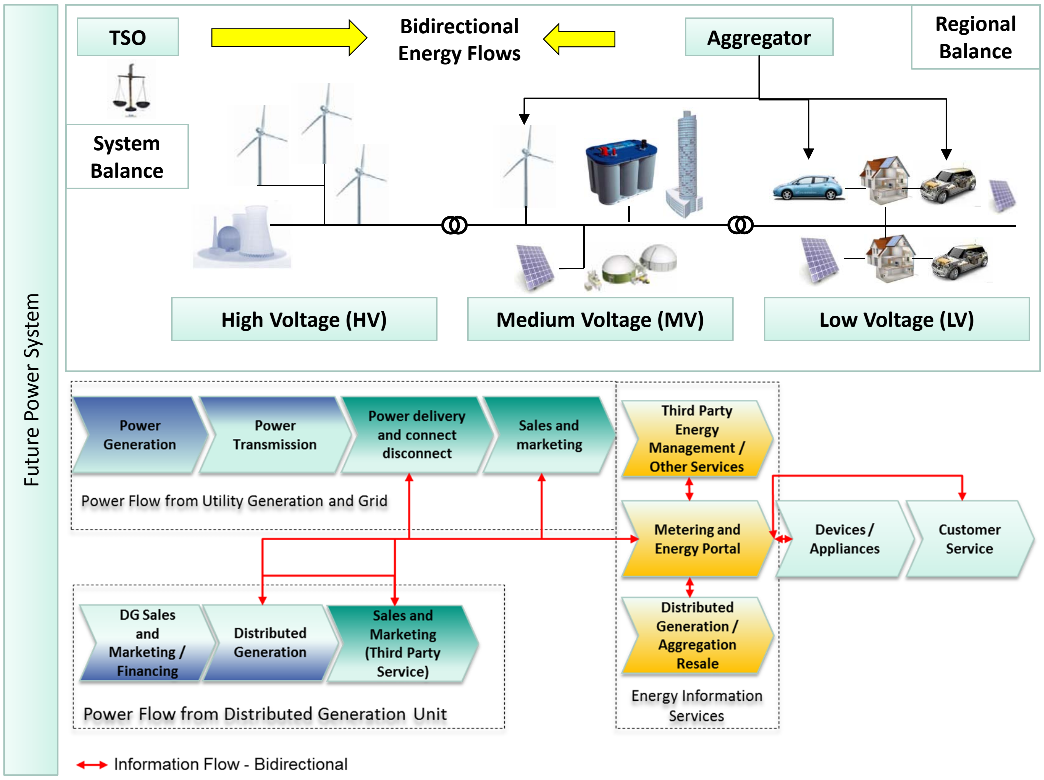


Figure 2.4: Structure, generic value chain and information flow of the future power system. Own illustration according to (Valocchi et al., 2007).

thus simplify system operation (Chalkiadakis et al., 2011). Residential customers which also generate their own electricity, the so called "Prosumers" could also participate in these clusters. This type of residential customer could also decide to become more self sufficient by managing his own demand to map his intermittent generation (Ramchurn et al., 2012; Sioshansi, 2011). Electric Vehicles are potentially very important in this environment, as their demand flexibility can be used to integrate intermittent sources. In addition they could also provide short term back-up power to the residential area they are situated in, or even participate in ancillary services markets in a V2G contract scheme of an Aggregator contributing to a physical regional energy balance, cf. Figure 2.4. All these developments are altering the traditional value chain of the power sector and involve new (local) actors, like Aggregators, who can provide energy from their DERs or bundle load and storage capacity so that a participation in the wholesale markets is possible and profitable in different application scenarios. The structure of the future power system is thus clearly defined by a bidirectional flow of energy enabled by a bidirectional flow of information and the according services (e.g. metering, energy management and DER bundling and resale), cf. Figure 2.4.

2.3.2 Challenges of the Smart Grid

In order to harvest the proposed benefits of the Smart Grid there are a variety of challenges in development of technology, standards and in particular regulation that need to be addressed. Technology, plays the crucial role of an enabler, but also imposes requirements for standardization in order to safely deliver the desired results. In particular the different actors in the Smart Grid need to specify standardized architectural concepts, data models and communication protocols in order to achieve interoperability, reliability and security between and for every single component connected to this "system of systems" NIST (2012); Arnold (2011). In addition further evolution needs to be accounted for by extension capabilities in the chosen protocols. These efforts need to be coordinated and standards and accompanying regulation must enhance innovative and open solutions in order not to introduce new market barriers to entrants in the power sector. Organizations like the National Institute of Standards and Technology (NIST) in the U.S. or the DKE /VDE in Germany (German Comission of Electrotechnics and Information Technology in the Electrotechnical Society) in coordination with IEC are focusing the respective efforts of numerous actors from different industries and stakeholders.

The power sector used to be more conservative in its decisions as disruptions in supply can be very costly and potentially dangerous for the economy and the regions affected. Therefore most power systems have redundant components and can also be operated above normal operation limits for a limited time. Also the investment cycles and volumes are higher than in the IT-industry, as generation and transmission and distribution equipment needs to be operational for several decades without severe failures during this time. Therefore the architecture of the Smart Grid and the integration of ICT in the existing structures must be designed and implemented with diligence taking into account the high security and reliability requirements of the power system. Figure 2.5 shows a conceptual reference diagram of NIST for the information networks and the general connections that need to be established between different actors. Implementing these structures is not a trivial task, as changes have to be done during ongoing operations and standards for legacy equipment of all kinds need to be taken into account. A reference model like this helps to create a common semantic understanding and a common language for the diverse set of actors. In Figure

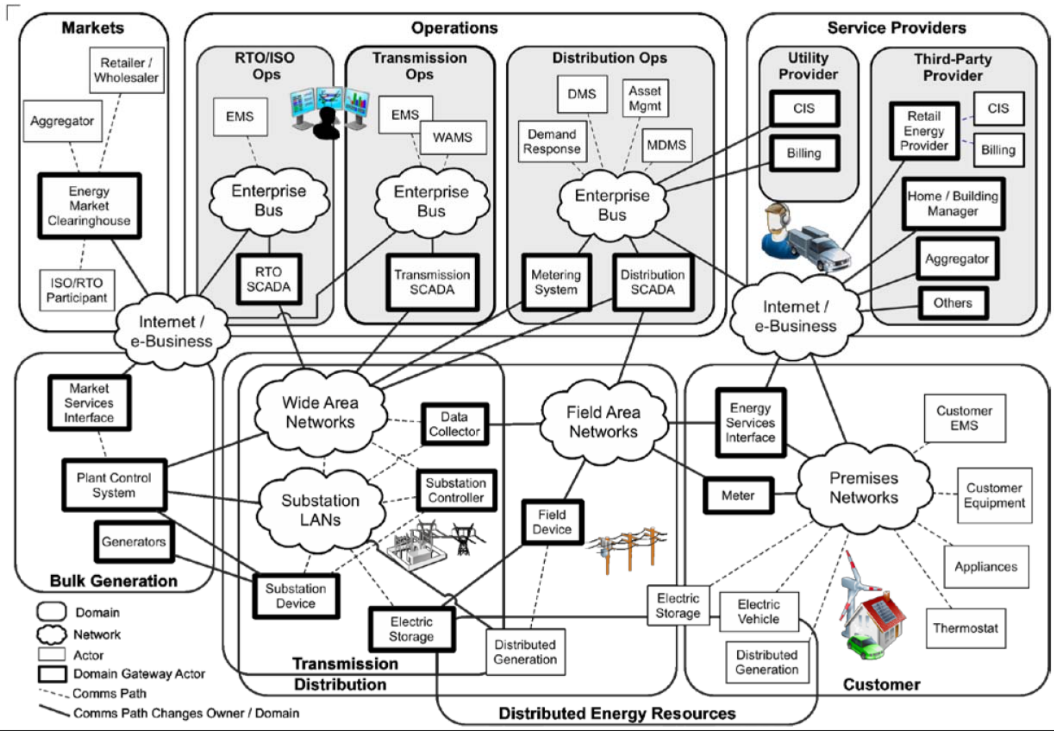


Figure 2.5: The NIST Reference Diagram for Smart Grid Information Networks (NIST, 2012).

2.5 it can also be observed, that there are various communication channels that have different latency and security requirements, as for example system operation and generation control have as compared to residential metering data only employed for billing.

Besides relevance to system critical operations, security and privacy need to be considered from the very beginning in the design of the Smart Grid and its systems. Security in this case mostly refers to cybersecurity, as the new connectivity of generation or controllable loads opens up the possibility of unauthorized access and a following severe disruption of service and high negative system impacts through coordinated cyber-physical attacks. Therefore cybersecurity in the power industry must not only cover the protection of information systems from unauthorized, access, use, disclosure, modification or destruction in order to provide confidentiality, integrity and availability. Cybersecurity for the power industry must also address security measures for the legacy automation and communication systems, in addition to implementing management, operational and technological procedures that account for the high reliability and fail-safe requirements of the power system (NIST, 2012).

Furthermore the privacy of residential and commercial customers needs to be respected and enforced by Smart Grid standards and its infrastructure. Especially for the residential sector, smart meters allow for a more transparent analysis and feedback of consumption behavior, but also enable utilities or third-party entities that operate the energy management system in a location, to obtain very sensible information about daily habits and usage profiles of certain appliances employing techniques like NIALM (Non-intrusive Appliace Load Monitoring) in a customers home (Zeifman and Roth, 2011). As stated before, non-authorized entities could also gain access to this sensible data and apply similar profiling techniques in order to enable further physical intrusion to the site, as one possible scenario, or the manipulation of meter data by the meter owner to lower costs, being another. These problems need to be considered on one hand by regulation, which needs to provide a legal frame that enforces privacy protection by default and on the other hand by technological measures like, secured hardware and hierarchical access rights for metering data, which enable each entity to obtain the level of detail of the data that it requires for its operations (Raabe, 2010; McDaniel and McLaughlin, 2009).

Finally maybe one of the most important challenges for regulators is to create an environment and establish incentives so that private investments can initiate a steady path of incremental transition to the Smart Grid (DoE, 2012; Appelrath et al., 2012).

Even though the Smart Grid is predominantly defined by its technical properties, the requirements from and the implications for power markets are a very important aspect of the Smart Grid concept. The communication and control capabilities enable a variety of coordination paradigms, each with its advantages and disadvantages for certain applications. The coordination of demand resources can for example be guided only by technical requirements, or on the other hand be organized by inclusion in a market based system, where demand bids are included for price determination and market clearing. The Smart Grid must enable Smart Markets that include locational system constraints and demand side bidding from an considerably higher number of participants than it is the case today in the exchange and pool-based markets. Regional energy markets could also be part of this solution (BNetzA, 2011).

The projected benefits of the Smart Grid predominantly result from its role as an enabler. It enables the integration and real time control of distributed and intermittent generation resources. It enables customers to learn more about their energy consumption, general behavior and flexibility potential. It enables more efficient power market transactions, not only from a technical perspective, but also from an economical perspective, as the demand side elasticity is strongly increased, for the first time ever since the installation of power markets. The Smart Grid offers the opportunity to lower transaction and coordination costs in the system and empowering the concept of Demand Response, as will be explained in the next section.

2.4 Demand Response

Demand Response (DR) is a concept first introduced to power systems in the 1970s following the 1973 energy crisis. At the time the significant oil price shocks lead to an increased awareness about energy consumption and energy efficiency. The U.S. pioneered in the advancement of this concept by imposing strict programs for energy conservation and demand-side-management measures on its integrated utilities at the time (Sioshansi and Vojdani, 2001). The programs had their focus on increasing overall energy efficiency, hereby reducing overall demand for energy, and on reducing peak load by enabling large industrial customers to reduce or shift a significant part of their load in order to stabilize the power system. The general load reduction would also contribute to a decrease of needed installed capacity to secure supply at all times. But as demand still varies over the course of every day in a system, and also varies in dependence of weather and season, a considerable number of reserve and peaking generators, often with comparably higher variable costs are needed to allow for the system to function properly. Demand Response is a crucial concept to increase the efficiency of the power system and can be defined as:

> *"..all intentional electricity consumption pattern modifications by end-use customers, that are intended to alter the timing, level of instantaneous demand, or total electricity consumption."* (Albadi and Elsaadany, 2008; IEA, 2003).

Demand-Side-Management (DSM) is part of the more general concept of Demand Response and is mostly referred to with respect to the explicit measures of utilities that were implemented for larger customers to contribute to technical system stability in a centrally controlled power infrastructure (Cooke, 2011). The term is still employed for these measures, but is also used synonymously for artifacts that in the following will be described as parts of Demand Response. The potential of Demand Response in electricity systems has increased with the advent of the Smart Grid concept, as ICT is lowering the transaction costs to include a large portion of the available load flexibility, which until now could not be integrated in the operation of the power system and the power market.

2.4.1 Advantages of Demand Response

The possible advantages of DR are manifold. Depending on its particular implementation an increase of demand side flexibility can help to reduce the generation reserves that are required to provide reliable supply. This is because peak demand can be reduced by load shedding and shifting of customers who have a higher flexibility and are willing, provided a certain reimbursement, to reduce their load so that all other loads can be satisfied and the system balance remains intact (Strbac, 2008). Depending on the power plant technology employed for generation, DR can thus contribute to reduce overall emissions, as additional coal or natural gas is not utilized for power generation.

Besides allowing for a higher utilization rate of available generation resources, DR can also help to increase transmission and distribution network investment and operation efficiency. DR on the transmission level could help to alleviate market power of single generators at certain congested locations and so called out-of merit dispatches of generators that serve loads in these areas, even if more economic capacity is available outside (Strbac, 2008). In distribution networks DR can help to defer network investments in new capacity, increase the amount of distributed generation that can be connected to the existing network, relieve voltage-constrained power transfer problems, and congested substations. Maybe one of the most important advantages of DR in the near future can be its ability to support the integration of intermittent energy generation sources like wind and solar. Without DR the power system balance in systems with high intermittent generation ratios, needs to be provided by a certain amount of conventional generation acting as a reserve to restore supply if sudden generation reductions occur. DR can help to reduce a part of these reserve power plants as it contributes to system balance by redistribution and reduction of the amount of energy consumed. In contrast to generation reserves, DR can also call on flexible loads to prepone their consumption which is especially valuable at times of high intermittent generation and low general load and this way increases the share of renewable energy used by demand (Strbac, 2008).

Besides the technical advantages for the power system, DR can contribute to make the demand side in power markets more elastic in economic terms. Ever since the introduction of market based systems for the allocation of gen-

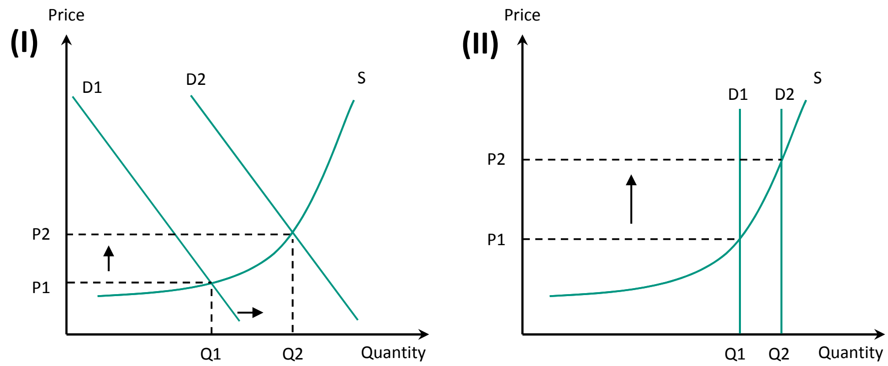


Figure 2.6: Demand and Supply in Normal Markets (I) and Capacity Constrained Markets (II) with Perfectly Inelastic Demand, adapted from (Sioshansi and Vojdani, 2001).

eration resources, the demand was considered to be fixed and given and had to be served under nearly all circumstances (Kirschen, 2003). This leaves the power market with only one side of the market capable to adapt to changes in demanded quantities of energy: the generation side. In particular this also meant that with increased demand, variable generation prices of the marginal generation unit in uniform (or reference) price based markets would increase significantly, as successively the demand would needed to be served by more expensive, or less efficient generators. This dispatch order according to marginal generation costs is commonly referred to as the merit order. Electricity markets can thus be described as generation and transmission capacity constrained markets with a (perfectly) inelastic demand side. The difference between a normal market with elastic demand and the power market with capacity constraints and inelastic demand is sketched in Figure 2.6.

In normal markets (I), demand would react to price increases by reducing the quantity purchased at this given price level (reduction of Q1-Q2), or increase its demand if prices are reduced (increase from Q1 to Q2) taking into account a moderate price increase. In the capacity constrained power market (II), supply levels approaching the system capacity limits are very expensive to provide. Even slight demand changes (Q1 to Q2) in this area can lead to considerable price increases (e.g. P1 to P2). This is in particular caused by the inelastic demand side which is not given the information about the actual price level for generation, but instead is charged an average price rate accounting for most of the normal variations in supply costs. This lack of information and in addition, real time metering prevented the demand side to play an active role in power markets so far. Systems to enable loads to react to variable generation prices and to meter them in real time have become increasingly more available and less expensive through the development of ICT and especially through the communication infrastructure of the internet. The demand side can thus be enabled by Smart Grid technologies like Smart Metering and automation to finally play an active role in the power market, (Stoft, 2002; Sioshansi and Vojdani, 2001)

2.4.2 Demand Response Classification

Demand Response can be classified in two general categories: Incentive Based Programs and Price Based Programs (Albadi and Elsaadany, 2008), c.f. Figure 2.7. The classical Incentive Based Programs rely on specific payments or rebates to predominantly large customers to reduce demand on a predefined number of days for a year or in case of system emergencies by allowing direct load control through the utility or providing interruptible loads. Market Based Programs are assessing demand reduction based on market prices for the particular energy or capacity products. They cover different time scales from mid-term capacity security to emergency and ancillary services (AS). Demand bidding can be implemented e.g. in day-ahead markets. These bids are ordered with the lowest bid being called first, similar to the generation merit order. All demand side bids are being paid the marginal demand reduction bid price of the particular time interval (IEA, 2003). In capacity market programs customers need to specify pre-defined load reductions when system contingencies arise. In ancillary service markets, participants are allowed to bid on the spot market as operating reserves and must fulfill their bid if called upon incurring a penalty if nor following the specified load reduction (Albadi and Elsaadany, 2008).

Price Based Programs for Demand Response are characterized by the fact that they reflect the actual costs of energy provision to the customers, simplified like in a Time-of-Use (TOU) scheme, or in a more detailed way in a Real-Time-Pricing (RTP) measure. Price based programs are thus different to most of the incentive based DR programs with regard to the fact that the actual decision to participate in demand reduction or increase is not located with the offering utility or the respective system operator, but with the individual customer. In a first step a TOU scheme would encompass a two-part tariff with the same peak and off-peak times for every day, charging a higher and lower rate, respectively. This scheme is particularly advantageous to get consumers adapted to dynamic rates, and to (manually) shift larger loads to off-peak times. It does not provide an opportunity to dynamic reactions to system contingencies.

Demand Response Programs	
Incentive Based Programs	**Price Based Programs**

• **Classical Programs**
  • Direct Load Control
  • Interruptible Load
 	
• **Market Based**
  • Demand Bidding
  • Emergency DR
  • Capacity Market
  • Ancillary Services Market
	• **Time-of-Use**
	• **Critical-Peak-Pricing**
	• **Extreme Day CPP**
	• **Extreme-Day-Pricing**
	• **Real-Time-Pricing**

Figure 2.7: Demand response program classification (Albadi and Elsaadany, 2008).

Critical-Peak-Pricing (CPP) and Extreme-Day-Pricing (EDP) in contrast can map system contingencies and inform customers about upcoming shortages on a day-ahead basis. CPP is incorporated by imposing rather high rates for particular hours of anticipated shortages, but still remaining in the other flat or TOU-scheme for other hours. In the CPP, and EDP schemes whole days would be declared to incur higher costs. These Price Based Programs can reflect the actual generation costs in a better way, so that customers can choose to use less energy or shift usage to other, cheaper time slots.

In economic terms Real-Time-Pricing (RTP) is the most efficient pricing strategy, as it can almost always send the right price signals to the demand side, for every hour, or even smaller time intervals in real time markets with e.g. 5 minute clearing intervals (Borenstein, 2005). Due to complexity residential customers are more likely to face only hourly changes, being announced on a day- or hour-ahead basis. RTP enables customers to make an informed decision about their energy consumption, provided the basic knowledge about their consumption patterns, and allows them to choose whether some of it can be shifted to other times, enabling significant savings, but also on the other hand eliminating some of the subsidies to high peak load customers at peak times, that did not have to face most of the costs they caused to the system. As RTP is capable of responding and mapping dynamic system conditions it is one of the main concepts employed later in this analysis with respect to its application for EV charging coordination.

2.4.3 Demand Response Challenges

Even though DR has many benefits there are a number of challenges that need to be addressed. They include technological, regulatory and social changes that need to persist in the power system in order to allow for the full potential of DR to unfold. One of the main technological challenges is the installation and correct operation of real-time metering and automation systems. Smart Meters are one possible solution to this challenge, but their metering information must be communicated to the different roles like Demand Side Aggregators, ISOs and RTOs employing standardized and safe communication channels in order to allow for real-time operation of the system. In particular the actual load reductions must be documented in order to assess their impact economically. A fact which in some classical DR programs based on standardized baselines (e.g. fixed demand schedules) constituted a problem for correct assessment in the past (Sioshansi and Vojdani, 2001).

Including a high number of new actors with flexible loads in the power system, will increase the coordination complexity. Therefore standardized communication protocols and coordination mechanisms must be put in place in order to allow for the DR potential to unfold. Especially the transaction costs for integration of flexible loads must be lowered so that DR can be also viable when compared to conventional alternatives to address peak load and distribution and transmission network congestion situations. This particularly means that DR must be more competitive than generation and storage equipment that is placed in congested areas (but might have low utilization rate), or the build up of additional network infrastructure. Assessing the economic value has proven itself to be quite challenging as its costs can not be defined as easy as in the case of generation, but highly depend on the location and the predominant network conditions. DR was proven to have more value in power systems that have rather inflexible generators with an increasing share of intermittent resources. In systems with a higher ratio of flexible generation, DR must be competitive to these resources if network congestion is not a limiting factor (Strbac, 2008).

When rolled out DR can be implemented in different ways, most of them will include a certain amount of automation technology which ensures a certain level of demand shifting based on prespecified values or on the preferences set by the respective customers. In the residential sector numerous field experiments show that customers are able to change a significant part of their peak load (about 10 % on average), and reduce overall demand (about 3-5 %) even when only relying on TOU tariffs and manual operation (Darby, 2001; Darby and McKenna, 2012). Continued observations also imply that employing automation technology according to user preferences in "set and forget" fashion will yield higher peak load reductions, higher response rates and energy cost savings, but also need to account for user acceptance of automation technology (Hammerstrom et al., 2007). Educating customers about the benefits of DR when implemented with automation technology that respects the preferences of the users is thus key for a large scale adoption of this concept.

The Smart Grid concept has the potential to enable Demand Response at low general implementation and transactions costs. This in turn will help to integrate a higher share of intermittent generators, increase the system stability and finally tackle one of the most important flaws of power markets: the low or non-existing elasticity of the demand side. EV can be seen as a large resource for Demand Response as they bring with them a quite high flexibility for a considerable part of their overall demand. Power Markets will serve as the main coordination mechanism to settle the increasingly flexible demand side and the less controllable generation side and will thus be considered from a Smart Grid perspective in the next section.

2.5 The Role of Power Markets

The main distinguishing features of electricity markets are driven by the physical features of this good: the necessity for instantaneous production at the very moment of consumption, the rather expensive and to date insufficient capability to store electricity efficiently, the cost differences associated with every type of generation technology and production characteristics, and the natural monopoly character of transmission and distribution grids, which already have been highlighted in section 2.2.1 (Kirschen and Strbac, 2004; Erdmann and Zweifel, 2007). These properties have a profound effect of how power markets have to be organized[1].

Electricity thus can not be treated like other commodities. Markets and trading mechanisms can help to generally allocate generation to satisfy demand requirements, but are not fully capable to organize the real time operation of the system as the market mechanism would have to determine valid clearing prices at every instant of operation. Therefore Ancillary Services need to be provided by the TSO to balance generation and demand forecast deviations for real time

[1] For a comprehensive description of power markets and their fundamental economics, please consider (Kirschen and Strbac, 2004; Stoft, 2002).

operations, Stoft (2002). These resources in turn can be allocated for larger time intervals on a corresponding market. Other important specifics of power markets are that one particular generator cannot sell directly to a particular customer as the produced power is fed into the power grid which is operated as one synchronous entity. Following Kirchoff´s laws one customer (or sink) will always be served by the physically nearest source (implying the lowest resistance during transport), Kirschen and Strbac (2004). This load and generation pooling effect displays high economies of scale, as the system only needs to provide sufficient generation capacity to provide the overall system peak load, not all of the peak loads at the same time, as these are randomly distributed and do not often coincide.

The main determinants of power markets are the generation capacity and the demand that it needs to cover. As described in section 2.2 most power systems have been organized centrally with a focus on the requirements of the generation side. The demand side (in particular residential demand) often has been inflexible and uninformed about the costs caused by their electricity consumption in the system. Due to this, demand is often inelastic to quite substantial price changes occurring through adjustments in the structure of the generation side at different system load levels. The centralized system architecture, imposed in parts by the technical properties of electricity also fostered a centralized economic allocation mechanism: pool markets, or power pools. With the increasing liberalization of power markets other more decentralized architectures like power exchanges have also been introduced to organize the provision of electricity in a economically efficient manner.

2.5.1 Pool vs. Exchange Markets

In a power pool, one entity like the TSO collects information from all generators that are willing and certified to participate in the power provision of the power pool area with respect to their marginal generation and start up costs, their minimum run-times, their flexibility in generation output, no load costs and availability times. These informations are provided in a complex bid format by the generators. The system operator (SO) then computes the cost minimal set of generators that are needed so serve the forecasted (and mostly passive) load. The SO employs the Unit Commitment (UC) model, which also takes into account transmission line limits and resulting power flows from the computed solution in order to guarantee system stability. Usually the dispatch calculation is performed in a day-ahead manner, thus allocating most of the generation

Pool Market	Exchange Market
Advantages • Centrally organized by ISO or TSO • Pool market operator is responsible for power system operation • Higher system efficiency and reliability • Complex bid formats reduce dispatch risk for generators **Disadvantages** • Small and medium participants (e.g. demand resources) have less incentives to participate • Demand side is mostly represented by a (inflexible) load forecast • Conventional pool markets are not “real” two sided markets • Intransparent side payments for non-convexitities (e.g. non-linear start up costs) are necessary • High information requirements for efficient unit dispatch	**Advantages** • Demand is accurately represented • Decisions about procurement are decentralized, less central information is required for efficient allocation • Nodal prices can be provided easier than in pool setting • Interdependent different markets exist (OTC, Futures, Day-Ahead, Ancillary-Services) • Actors on the market can be unbundled **Disadvantages** • Market rules need to account for technical interdependencies to provide the reliability of a pool system • Coordination costs can be higher and result in less efficient system operation (i.e. start up costs) • All valid transactions with physical fulfillment are reported to the TSO

Figure 2.8: Comparison of pool and exchange markets, adapted from Stoft (2002); Kirschen and Strbac (2004).

needed for every hour of the next day. The complex bid formats for pool markets encompass non-linear cost terms and operation constraints as well as additional operation options for the provision of AS and in particular regulation energy. This complex bid format has the advantage that the bulk power provision and the provision of operating reserve and regulation that is needed on a short time scale are co-optimized based on the same set of resources under consideration of grid constraints. This allows for a technically well coordinated and efficient operation, but also has negative implications resulting from the complexity of the bid format. In particular side payments or "whole"-payments that are paid to generators that are needed in certain load configurations, but are not awarded their bid in the first UC-solution, open the possibility of untruthful individual behavior in order to increase generator profits. In addition complex bid formats mostly do not incorporate the possibility of active demand side participation (Kirschen and Strbac, 2004). Power pools are thus advantageous for a technically optimal operation of a power system, but have high centralized information requirements which make it increasingly complex and possibly challenging to apply their operation architecture in highly decentralized Smart Grid settings.

Power exchanges are a more decentralized coordination institution that build on (uniformly) determined prices to signal the scarcity of electricity for the respective periods traded. Exchanges are centralized insofar as they provide a reference price for the provision of electricity in a particular time frame. Several exchanges can exist in parallel, but as power generation is mostly coordinated in a clear regional context due to the natural monopoly characteristics of the power grid, only one power exchange is operated in a region. Besides the allocation of demand and supply on the power exchange on a short term (several weeks - hours ahead of delivery) long term contracts, in particular futures and delivery options can be traded (c.f. Figure 2.9). In parallel to this bulk power generation allocation the provision of ancillary service is organized e.g. in Germany employing a reverse auction platform on which certified generators can submit bids for positive and negative regulation products according to the amounts expected by the TSO.

Technical interdependencies between the different products of day-ahead and ancillary service markets must be considered in the market design and its rules in order to allow for an efficient system operation. In addition products must be designed in such a way that particular generator types can bid accordingly (e.g. inflexible base load plants that place block bids in the spot market). If these interdependencies are not considered appropriately the market outcomes can lead to additional redispatch costs and thus less efficient system operations up to the point of a decreased reliability of supply (Stoft, 2002).

Figure 2.9 provides an overview of the general electricity markets and products in Germany. A considerable part of the bulk power generation is sold in bilateral contracts for several years ahead, forming the futures market encompassing products with physical and financial fulfillment. These trades can, but do not necessarily have to, be registered with the power exchange in Germany, the European Energy Exchange (EEX). The EEX offers trading possibilities for futures in a standardized manner, and also operates a spot market. Bids can be placed from 14 days to 45 minutes before delivery for hourly products and block products. The reference price determination takes place in a central call auction at noon on the day before delivery. This *day-ahead* auction and the resulting prices for every hour of the next day thus represent most of the expectations of all market participants about demand forecasts, renewable energy generation and power plant availability. Corrections to this can be made in a continuous *intra-day* auction until 45 min. before execution which allows to consider new information and handle uncertainty efficiently (Kroneberg and Boehnke, 2010; Grimm et al., 2008,?). Ancillary services are traded on a different platform that has been harmonized with the trading times on the EEX, thus accounting for the

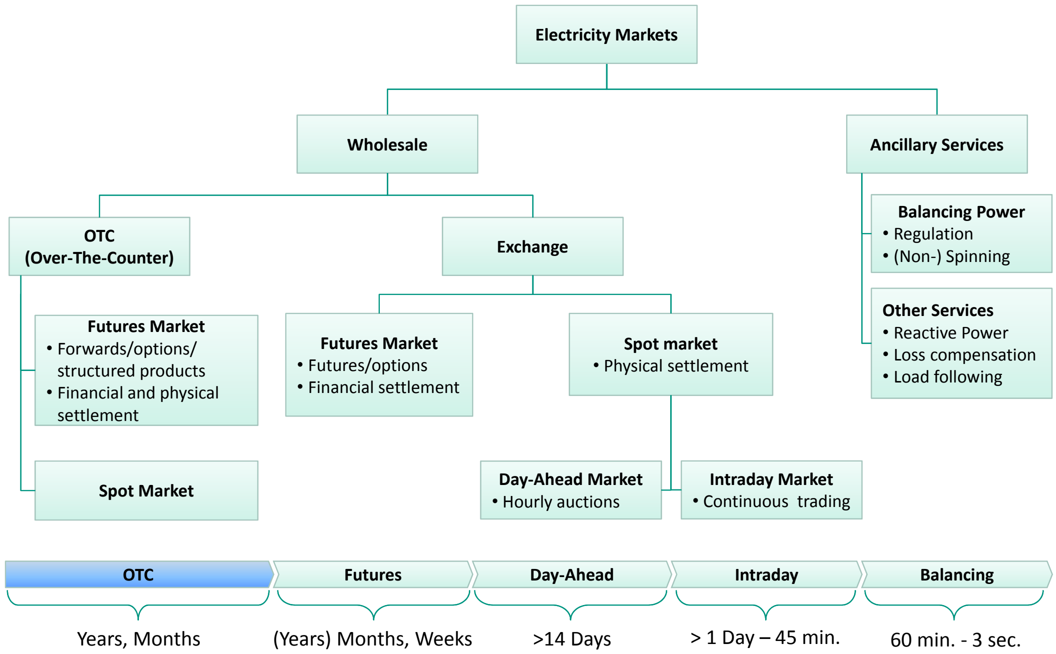


Figure 2.9: Structure and time frame of the interdependent electricity markets in Germany and their main products (Judith et al., 2011).

interdependence of short term (re-) dispatch decisions.

Power exchanges can produce economically more efficient outcomes than pool based systems only if they are well designed and account for transmission constraints and interdependencies of the products traded (Cramton, 2003). They provide adequate scarcity signals for the demand side and enable the participation of demand resources. Power markets need to consider a number of complex interdependencies which need to be evaluated for every particular case individually. The next section will therefore address the concept of prices for power systems control.

2.5.2 Prices for Power System Control

Employing prices as the central coordination element in power systems is a concept first introduced in the seminal work of (Caramanis et al., 1982; Schweppe et al., 1988). Even at this early stage of automation and only in the beginnings of advanced telecommunication networks Caramanis et al. (1982) envisioned a power system with a more dynamic demand side and economically efficient *spot prices*. The concept of spot pricing encompasses the notion that for every given region or node, or more particular for every customer there is an optimal spot price that is maximizing total welfare. The optimal spot price for real and reactive power was thus defined as:

$$P_{spot,opt} = MC_{fuel} + EBal_{QoS} + TD_{QoS} \tag{2.1}$$

This spot price does not distinguish between different roles in the power system, but represents the cost for the provision of or the revenue for generating a specified amount of energy at a particular time and location. In conventional power systems, this price is mainly determined by the marginal generation cost which in turn depends on the fuel used by the marginal generator MC_{fuel} in the so called merit order of economic dispatch (c.f. Figure 2.10). In addition to the generation costs, a price premium accounting for system stability and in particular the energy balance $EBal_{QoS}$ ensuring the quality of supply in the power system is paid. The energy balance component is zero as long as there is surplus generation and line capacity available to cover additional demand. If contingency situations arise, this mark-up is the difference between the incremental value of electricity usage for the incremental customer and the marginal fuel cost. The third mark up on the price is the transmission and distribution quality of supply fee, TD_{QoS}. The T&D fee varies in dependency of the voltage situation and the line utilization factor. It can be negative or positive as it depends on the current local grid situation. The T&D and the energy balance mark up can be different for every customer. Deviations are likely to be higher for lager customers, as they depend on grid architecture and the individual load and thus the corresponding line losses and voltage levels also vary (Caramanis et al., 1982). Without congestion and in perfect system balance all customers would see the marginal fuel cost price. The spot pricing concept thus also builds on the notion of uniform pricing for generation, but enhances this widely recognized pricing regime by the notion of locally differentiated discriminatory pricing that reflects the actual system status and contingencies.

Centralized structures still shape exchange and pool markets, and the demand side still suffers under the two main demand side flaws: the lack of real time metering and billing and the resulting lack of reaction to price changes (c.f. Chapter 2.4) as well as the lack of real-time power flow control to specific customers (not permitting for the enforcement of bilateral contracts and making the TSO the default supplier in real-time) (Stoft, 2002). In particular the first demand side flaw can be ameliorated by smart grid technologies and applications and finally allow for the stepwise realization of the spot pricing concept incorporating an active and informed demand side.

In order to inform the demand side and set incentives for Prosumers [2] to adapt their consumption and change their role in the system to a net generator, the valid spot prices for a time period must be communicated. Caramanis et al. (1982) envisioned that spot prices should be determined in five minute intervals which required the customers to have a constant real-time communication connection with the utility in order to react to price changes. This is now technically easy to implement and partly implemented in the determination of LMPs in real time markets, but was visionary at the time. Since the metering and communication costs do not justify to put all customers on real-time spot pricing, approximations on a daily and/or monthly basis of at least hourly changing prices (so called predetermined prices) that reflect the general system cost structure are the most viable solution for practical implementation of dynamic spot pricing. The TOU-rates described earlier are the well known and now increasingly applied tariff model for these predetermined prices.

According to (Schweppe et al., 1988) each customer is free to select his pricing regime, as he must be able to assess whether he can adapt his demand behavior in such a way that a participation is beneficial for him. Significant demand side flexibility potential has been harnessed in the industrial sector, lower transaction costs could further increase the contribution of the commercial and residential sector for demand side flexibility. In addition new loads like EVs can substantially contribute to the increase of overall demand elasticity.

Employing prices for power system control can be beneficial from an economic perspective, nevertheless a purely price based system operation is likely to be to slow to ensure the physical stability. Alvarado (2005) reconsiders the different possibilities to control power systems by price signals. The most common concept in this respect are LMPs which are often based on optimal power flow calculations and incorporate main aspects of the spot price concepts postulated above. In contrast to the spot concept LMPs nowadays do only incorporate a passive demand side. Depending on the particular design of the power market, Alvarado (2005) shows that for known generation costs, market participants would converge to an optimal dispatch order without the need to be aware of any congestion relief efforts of the system dispatcher. The assumptions made in this approach do not consider strategic behavior (i.e. the execution of market power) of generators, but show in principle that a price based dispatch could

[2]The term *Prosumer* refers to a consumer that can also generate energy and thus change his net impact on the power grid (Ramchurn et al., 2012).

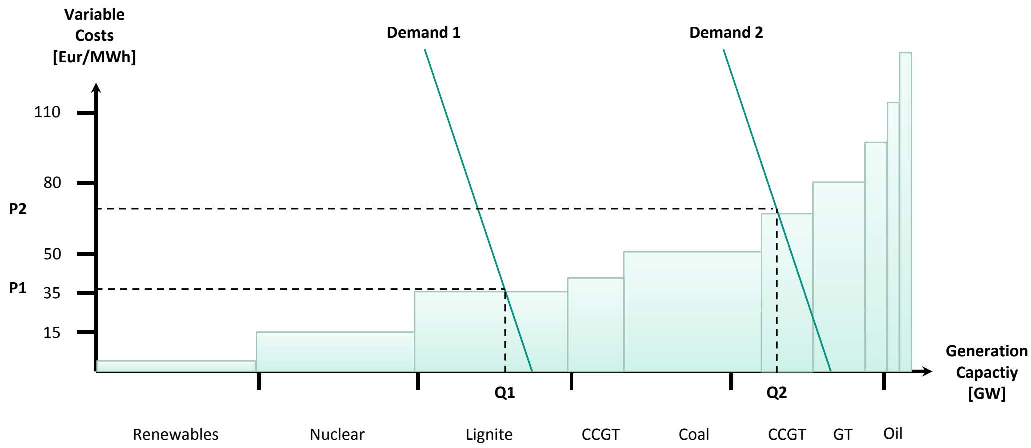


Figure 2.10: General structure of the merit order in Germany, adapted from Sensfuss et al. (2008).

be organized. When in turn the non-stationary cost structures of generators and especially delays in response dynamics are considered, a delay in the system output could lead to oscillations that could endanger system stability. Power system control by prices is possible but needs careful consideration of the physical requirements if real time operation is envisioned. Before this considerable parts of demand can be incentivized to adapt to main system contingencies and resource availability.

Prices can also be employed to map the availability of renewable and fluctuating generation in the power system. In Figure 2.10 the stylized structure of the German generation merit order is depicted. Following Sensfuss et al. (2008) the considerable increase in renewable generation production with very low variable costs leads to lower costs for the particular hours with high renewable output, which is e.g. the case for PV during noon. In Figure 2.10 this is depicted by the shift from *Demand* 2 to *Demand* 1 as the energy quantity that is covered by the conventional plants is reduced from $Q2$ to $Q1$. This well know *merit order effect* leads to lower wholesale power prices in the short run, but also might cause capacity problems in the long run as more expensive but flexible units can not recover their capacity costs only based on participation in the wholesale market Cramton and Ockenfels (2012); Cramton and Stoft (2005). In the short run (but also in the long run) more demand side flexibility is needed to stabilize the system. EVs have the potential to make a substantial contribution in this sector and will thus be analyzed with respect to their technical and demand response characteristics in the next section.

2.6 Electric Vehicles

Electric Vehicles (EVs) have a long history in the individual transport sector. In the humble beginnings of motorized individual transport in the late 19th century EVs were one out of three technologies for propulsion of motorized vehicles that were deployed. The alternatives were steam powered vehicles and petrol driven internal combustion engines. Advancements in technology, the higher energy density of petrol as well as its relative low price changed the odds in favor of the now conventional internal combustion engines (Larminie and Lowry, 2003). Ever since then EVs have been prevalent in niche applications that did not require extensive range or had strict local emission regulations. Since the 1970s and the oil crises, the development of EVs was given new attention, as different technologies for personal transport, which did not depend on oil as an energy source were gaining new momentum. But it was not until the 1990s that EVs started to be more popular again with a prominent example on the streets being the GM EV 1.

With an increasing public and political awareness for resource conservation and the need to reduce greenhouse gas emissions, electric vehicles were coming back on the streets after the year 2000. Rising fuel prices and significant advancements in battery technology, in particular for Ni-Mh and Li-Ion technologies enabled the development and large scale adoption of hybrid electric vehicles (HEVs). This development continues nowadays with the introduction of plug-in electric vehicles (PHEVs), which can be recharged by the power grid, but still have a range comparable to internal combustion engine vehicles (ICEVs). The last step, the deployment of full electric, or battery electric vehicles (EVs) is now supported by political institutions nearly all over the world (IEA, 2011). Nevertheless one of the main drawbacks of this technology that needs do be addressed is the high cost for energy storage.

2.6.1 EV Development and Opportunities

Electric vehicles are a crucial technology to reduce the general dependency on oil and also help to reduce local emissions. In addition one of the most important points in favor for electric vehicles, is that if they are powered by renewable energy sources their operative CO2 emissions can be reduced to very low levels. Transport energy consumption accounts for more than 53% of the world oil consumption and transport related emissions account for 19% of the worlds CO2 emissions (Garcia-Valle and Lopes, 2012). In Germany the transport related

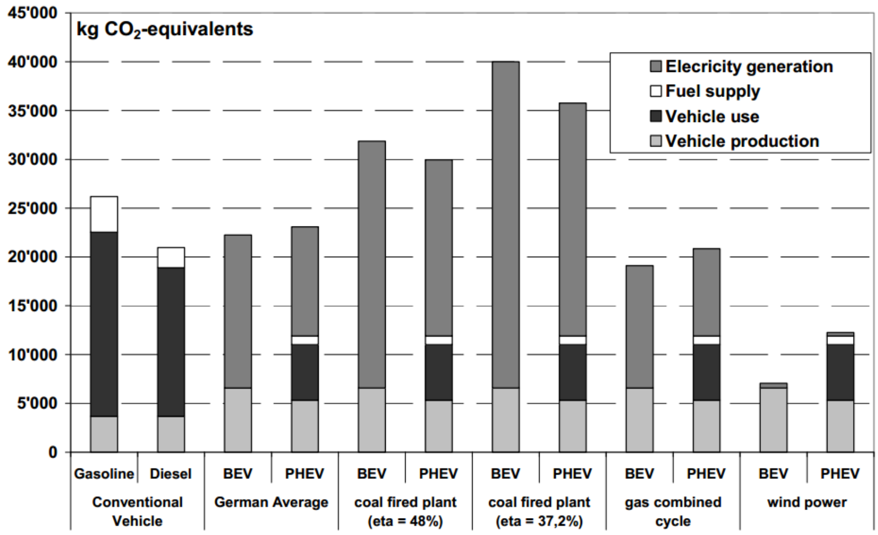


Figure 2.11: Emission comparison of conventional and electric vehicles in dependence of power source used (Helms et al., 2010).

emissions account for 18.7 % of the CO2 emissions and are thus on a similar level (UBA, 2012a). EVs can contribute to reduce these emissions, as more than 50% of transport emissions are caused by light duty vehicles (Rodt et al., 2010). Depending on the source of energy, EVs can have a different carbon footprint, as depicted in Figure 2.11.

When compared with regard to their life-cycle emissions, a battery electric vehicle (BEV in Figure 2.11) causes only slightly less (more) CO2 emissions as a comparable conventional gasoline (diesel) vehicle. This is due to the rather high share of lignite and hard coal generation in the German power generation mix, leading to a specific emission value of 538 g/kWh as of 2010 (UBA, 2012b). If only coal generation would be employed to charge the vehicle, the emissions would be nearly double as high as in the conventional case, rendering EVs with power provided from coal generators as one of the worst alternatives with respect to life-time emissions (Helms et al., 2010). When less emission intensive generation sources are employed to provide the energy for driving emissions can be reduced drastically. The reduction potential can clearly be seen in the case of wind-power. Besides the emission reduction potential EVs have more advantages but still also some challenges that need to be addressed. General advantages of EVs are (also partly applicable to PHEVs and HEVs, according to Naunin (2006)):

- No local emissions, which is beneficial for urban areas

- Little or no CO_2 emissions if renewable power sources are employed for charging (cf. Figure 2.11)
- Less noise than conventional vehicles at speeds below 30-50 km/h
- Higher overall energy efficiency (more than 70%, tank to wheel) as compared to 25% or less for conventional vehicles
- Ability to regenerate energy when braking, which also increases energy efficiency
- Electric engine has so called "instant" torque from the beginning, rendering EVs with dynamic trip characteristics
- Lower per km energy costs than conventional vehicles at current prices
- Storage and demand flexibility potential for the power grid, which is in the focus of this thesis.

There are still several drawbacks and challenges for EVs that need to be addressed, most of them due to the battery technology:

- Small range as compared to conventional vehicles
- High production/purchase costs due to expensive battery technology
- Lower energy density and higher weight
- Temperature sensitive storage technology
- Battery life time shorter than potential vehicle use
- Longer refueling times than conventional vehicles.

As considerable resources are devoted to battery technology development, the main challenges of EVs are currently addressed step by step. These developments will be described in the following sections. Before this, a more detailed description of the different classes of EVs and the definitions used in this work will be given.

The term EV is not unambiguously defined and must be clarified for the context of this work, cf. Figure 2.12. Electric Drive Vehicles (EDV) can be distinguished in supply line bound electric vehicles like trains, or trams and autonomous or grid independent vehicles. The autonomous vehicles can be distinguished in solar powered vehicles, battery electric vehicles and hybrid electric vehicles. Solar powered vehicles make the case for innovative modes of transportation, but are not applicable in daily operations. Battery electric vehicles which are sometimes also denominated full electric vehicles are EDVs which obtain their propulsion energy from one or several batteries. In this work the abbreviation EV will be used to refer to this sort of vehicles.

Hybrid electric vehicles have an additional energy source besides the electrical storage element, which provides energy for propulsion. This energy source

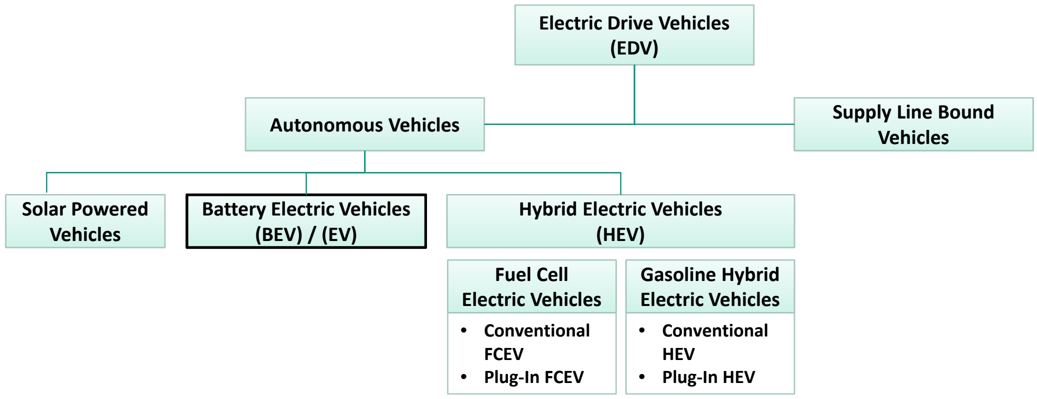


Figure 2.12: General EV classification, adapted from Larminie and Lowry (2003).

can either be a fuel-cell or a specific combination of a combustion engine and a battery, which is considerably smaller than the battery of an EV. Both hybrid vehicle types can be adapted to gain characteristics of an EV if the battery size is increased and a possibility for recharging from the power grid is included into their concept. These vehicles then belong to the class of plug-in hybrid electric vehicles (PHEVs).

Besides the various technical concepts which reflect different levels of drivetrain electrification and energy source, the different vehicle properties with regard to range requirements are likely to lead to a differentiation of EV application scenarios during the first phase of adoption. In order to enhance the development of EVs and their technology, the German government appointed a joint institution of involved stakeholders to coordinate the research & development of vehicle components with a focus on battery technology, industrial standards and processes, charging infrastructure and ICT based grid integration (NPE, 2011b). The political goal for Germany is to have 1 million EVs and PHEVs on the roads by 2020 (NPE, 2011b), cf. Figure 2.13. But as mentioned before there are still drawbacks that have to be addressed, before this technology will be able to keep its promises. The technological and economic challenges are major aspects, but one must also consider the EV-user or customer as another critical factor for success.

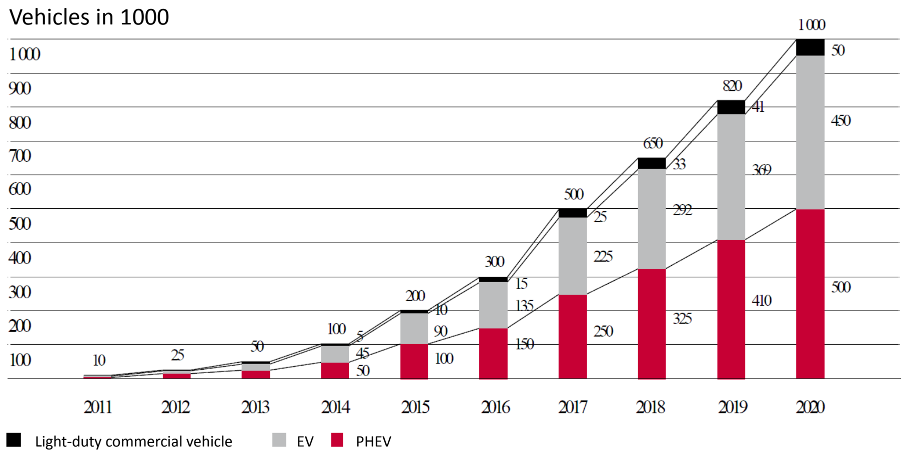


Figure 2.13: Expected development of EV numbers for Germany, adapted from NPE (2011b).

2.6.2 EV Mobility Requirements

When looking into socio-technical aspects of technology adoption that is bound to considerable capital efforts for the individual, it can be seen that new technology is expected to recover its additional costs in rather short time horizons. For fuel efficient vehicles studies conducted showed that customers expected the savings to recover their costs in less then three years, even though the actual payback periods could be more than double as long (Sovacool and Hirsh, 2008). Besides high expectations with respect to fuel efficiency, which also depends on the driving habits and behavior, the general usability of EVs must be quite similar to conventional vehicles in order for them to be accepted. In this context the limited range, as compared to conventional vehicles needs to be considered. The term *"range anxiety"* was coined in this context, reflecting the intrinsic fear of consumers to be forced to end a trip before their destination, or a lack of flexibility in their driving distance due to insufficient battery capacity (Hidrue et al., 2011; Turrentine, 1994). Additionally long charging times are also perceived as being a hindrance for a flexible mobility behavior. This particular concern has been addressed by manufacturers, as fast charging DC systems have been designed that allow to increase the SOC of a vehicle to 80 % in 30 minutes (ABB, 2012).

As for the range requirements it can be observed in several studies with a focus on individual travel behavior, like the National Household Travel Survey (NHTS) from the Department of Transportation (DOT) in the U.S., or the Mobility Panel Germany (MOP), that the average daily distances traveled can be ful-

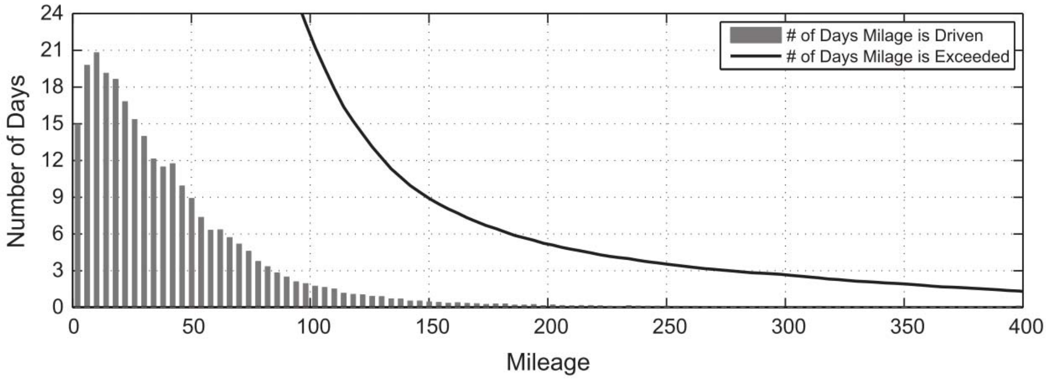


Figure 2.14: Average daily mileage distribution from Pearre et al. (2011), the solid line indicates the number of days on which the respective mileage was exceeded.

filled by standard EVs with a driving range of 100 miles, or 160 km for a majority of the cases. Further studies like Pearre et al. (2011) with individual GPS tracks of several hundreds of conventional vehicles generate a similar impression. In particular the daily mean driving distance observed in the NHTS survey is 29.1 miles (46.82 km) (NHTS, 2001). Pearre et al. (2011) observe a mean value of 32.6 miles (52.45 km) with a median value of 18 miles (28.96 km). These numbers are visualized in Figure 2.14, where it can be seen, that the most common average daily driving distance is between 12 - 16 miles (19.3 - 25.74 km). Also about 95% of all average daily driving distances are below 100 miles / 160 km. What is also addressed in Figure 2.14 is the number of days on which the respective maximum driving distance is surpassed, being represented by the solid black line. One must read the line as for example for 100 miles of daily travel distance to be surpassed about 23 days in one year in the sample of (Pearre et al., 2011). These events are likely not be covered by full EVs unless more expensive models with larger batteries are employed for driving. Following the results of the U.S. studies one can observe that most daily driving distances can be covered by EVs on average. For individual driving profiles that have longer daily trips or that can not adapt on 23 days of the year at maximum, EVs are not suitable. Adapting in this context means that they stop for charging, or choose a conventional vehicle for the respective trips. Thus (Pearre et al., 2011) conclude that EVs with a range of 100 miles / 160 km are suitable for 31% of the drivers if they are willing to make trip adaptations on 6 days in a year.

When we compare the daily average driving values from the U.S. studies with the MOP from Germany we can observe a similar distribution of average daily trip lengths, d.f. Figure 2.15. In this context it is important to emphasize that the

Table 2.1: Comparison of average daily driving distances of different mobility studies.

[km]	NHTS	Pearre et.al.	MOP
Mean	46.82	52.45	35.74
Median	-	28.96	24.71
95% Quantile	-	160.9	104.82

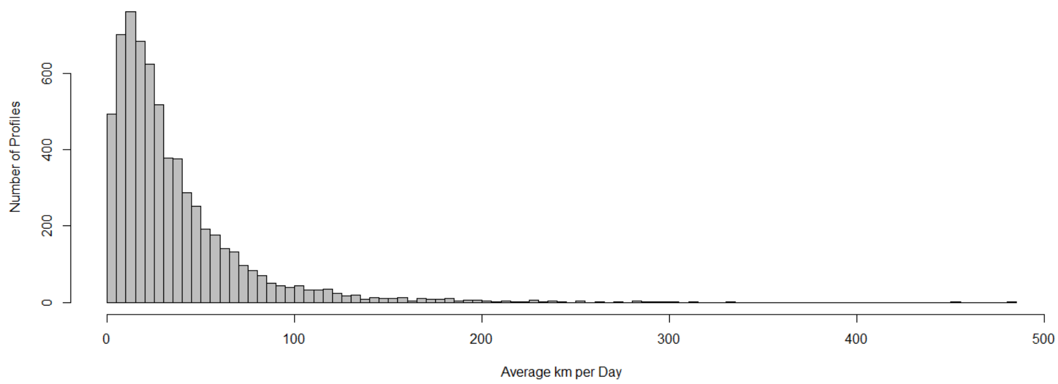


Figure 2.15: Average daily trip length distribution for a representative sample of 6466 driving profiles from the MOP (BMVBS, 2008).

sample data in the mentioned studies is collected in different ways. The NHTS is a survey based one day observation which is conducted for a high number of samples. The GPS based study from Pearre et al. (2011) builds on a longitudinal study of 470 vehicles being tracked for more than 50 consecutive days. The MOP in turn is a weekly observation of a predefined representative panel being repeated on a yearly basis. Nevertheless we can observe similar results when we consider the general distribution of trips.

In particular we see in the MOP that the majority of average daily trips depicted in Figure 2.15 for a sample of 6466 driving profiles (all profiles with a clear 1:1 mapping between vehicle and driving profile), which is partly employed for the simulation based analysis later in this thesis, is also below 100 km. The general driving distances are lower in Germany, as 95% of the MOP sample drive less than 105 km per day. It can be observed that 98.37% of the vehicles drive less than 100 Miles or 160 km per day. The median value for trip lengths in the MOP sample is 24.71 km, the mean value is 35.74 km. Following these empirical observations we can conclude that EVs are suitable for most driving needs. In order to address the mentioned range anxiety EV designs can also consider additional battery capacity for a *"range buffer"*, or the user can determine a SOC value, that when undercut, must be recharged at the opportunity. Kempton and Tomić (2005b) determine this range buffer to encompass 20 miles (32.18 km). Besides the range requirements, the applicability of EVs does also highly depend on their economic competitiveness. This is still a crucial factor affecting the development of EV deployment.

2.6.3 EV System Costs

EVs are still more expensive than conventional cars, for small city cars the difference in price can be as high as 100%. This is mainly due to the high costs of the storage components. When EVs are compared to other vehicle types, like diesel and gasoline ICEVs, Hybrids or PHEVs and FCEVs with respect to their production costs, one can see that they are one of the most expensive technologies, (cf. Figure 2.16 with values from Mock et al. (2010) based on 2009 production costs without learning curves.) Only FCEVs are more expensive due to lower production numbers and high valued materials like rare earths that are needed for the fuel cell components. The numbers presented refer to a mid-sized car and do not consider marketing costs and profit margin, along with sales taxes. Investment decisions concerning vehicles are not only made based on the initial cost, but also on the expected fuel efficiency and the related costs for operation. In this case the comparison with regard to the specific energy consumption per kilometer shows that EVs have a considerable advantage to other technologies. ICEVs have by design, as being thermal engines, a lower energy efficiency and range between 0.57 to 0.74 kWh per km. This corresponds to an average consumption of 6.5 - 8.4 l/100 km for gasoline and 5.8 - 7.5 l/100 km for diesel[3]. Hybrid and PHEVs are more efficient as they increasingly combine the advantages of both conventional and electric drive technology. The PHEV is listed in this context with 0.32 kWh/km (3.6 l/100 km) and the EV with 0.18 kWh/km (2.05 l/100 km), which is slightly higher than the average value from Table **??** of 0.151 kWh/km (1.73 l/100 km). The nearly three times higher efficiency of the EV can thus contribute to make it economically viable, despite the high initial investment.

A selection of available EVs produced in relevant numbers (at the time of writing of this document) shows (cf. Table**??**) that the average price is higher than mentioned in Figure 2.16. When excluding such exclusive cars as the Tesla Roadster, the average retail price is about 31,700 Euro. For many models (i.e. the ones

[3] Assuming an energy value of 8.76 kWh/l of gasoline and 9.8 kWh/l of diesel (Erdmann and Zweifel, 2007), p.183.

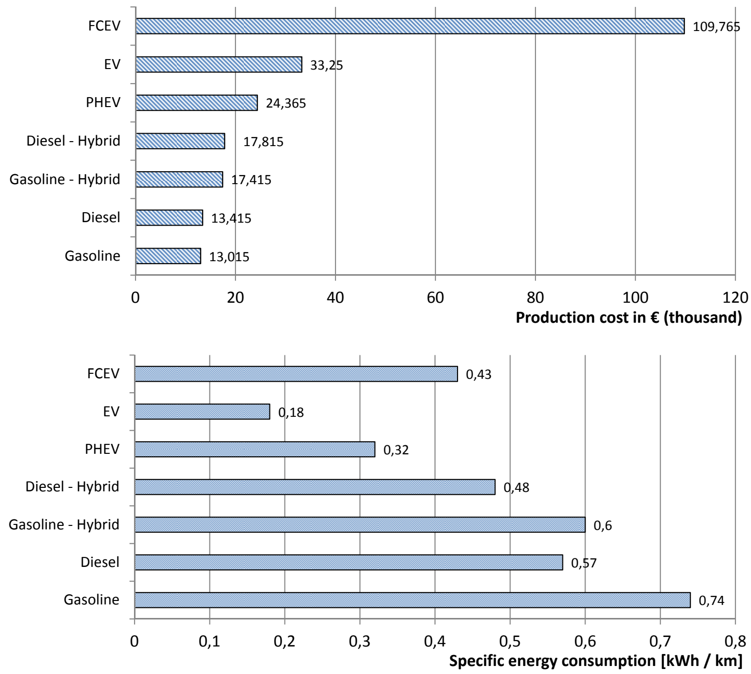


Figure 2.16: Construction costs of different vehicles types as of 2009 (top) and specific energy consumption per km (bottom) (Mock et al., 2010).

from Renault) and additional battery leasing fee needs to be payed on top every month which again adds to the operation costs of the owner, but brings a guaranteed life time for the battery and additional services. The battery size varies with the class of the vehicle, most batteries are around 20-30 kWh as this value represents a trade-off between the range requirements of the customers and the costs that increase disproportionally with the size of the battery.

If we focus on the main advantage of EVs in economic terms, their low per km costs, we see that when the price of energy for refueling is varied in a considerable range (cf. Figure 2.17) between 0.05 - 0.65 Euro/kWh, EVs are the most stable option with respect to operational cost control. For comparison the fuel price range for gasoline and diesel is placed in the respective part of the kWh price on the x-axis. Here we observe that EVs have per km costs of 0.045 Euro for a common kWh price of 25 ct (the average retail electricity costs in Germany for 2012 (BNetzA, 2012)), whereas conventional (gasoline) vehicles incur costs of about 0.14 Euro per km at the lowest current price levels of 1.50 - 1.60 Euro/l. Additional costs for maintenance are also lower for EVs, as they do not have as many moving parts and the electrical engine is also a rather simple component from its basic construction characteristics. Total cost of ownership analyses sup-

Table 2.2: List of selected available full electric vehicles from serial production with main properties and retail prices (January 2013).

Vehicle	**Range [km]**	**Specific Consumption [Wh/km]**	**Battery Capacity [kWh]**	**Retail Price [Euro]**
Mitsubishi iMiev	150	135	16	29,300
Renault Zoe	210	105	22	20,600
Smart ForTwo ED	135	130	17.6	23,680
Ford Focus Electric	160	143	23	39,900
Nissan Leaf	160	150	24	33,990
Renault Fluence	185	118	22	25,950
Tesla Roadster	350	160	56	128,520
Tesla Modell S	335	179	60	53,769 [a]
Renault Kangoo	170	130	22	20,000
Toyota RAV 4 EV	160	261	41.8	38,307
Avg. Vehicle	201.5	151.1	30.4	41,401

[a] Assuming an exchange rate of 1.3 USD/EUR.

port the finding that without major battery failures EVs can be cost competitive in the medium run. In particular this is likely when EVs are used more frequently, which could be the case in a car-sharing system, where the initial high capital costs are distributed over a higher number of users and longer distances driven (Contestabile et al., 2011).

Besides these economic and technical aspects, cultural differences in the individual valuation of a vehicle must be considered as an important factor for mass adoption of EVs. This means that EVs need to be perceived not only as small, economic "boxes" serving for mobility purposes, but need to have characteristics that people with the respective cultural background find attractive for a vehicle. In addition new application patterns for vehicles might also change the role of EVs, as mobility is gradually advancing to become a service that is not only being performed by one individual mean of transport, but by the one most suitable according to the preferences of the user. These inter-modal or multi-modal mobility patterns combine different means of transport, like transit, high-speed rail and car-sharing systems to deliver the best or most flexible trip itinerary. The role of the EV could thus also change and not merely reproduce the usage pattern of conventional vehicles, again contributing to a more resource efficient individual mobility.

In the following sections the technical properties of EVs will be addressed in more detail, with a focus on the different configurations of EVs, their storage technology and cost as well as their active role and integration into the power system.

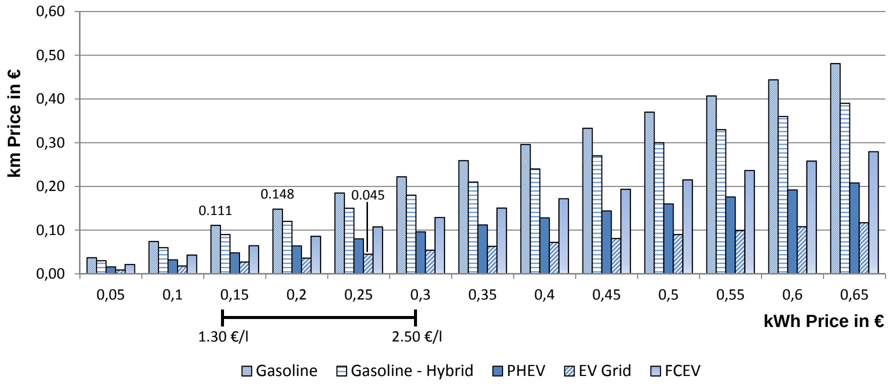


Figure 2.17: Energy related costs per km in dependence of kwh price for the main vehicle types, based on the specific consumption values from above.

2.6.4 EV Drive Train Concepts

In the previous section a general classification of EDVs has been performed. In this paragraph the essential technical architecture of different vehicle types is explained in more detail. In particular the drivetrain concepts of conventional, hybrid and plug-in hybrid, fuel cell and electric vehicles are compared with each other. Further more technically interested readers are referred to (Husain, 2010) and Appendix C.

The standard EV setup consists of a battery, a power converter which can work in both directions as energy is regained through regenerative breaking when the electric engine (EE) is working as a generator, and the according power electronics for control. FCEV which are powered by hydrogen or reformed on board from methanol. The hydrogen is used in the fuel cell stack to generate electricity that is either used for driving, or is stored in the on board battery. In both cases the battery is the only connection to the EE.

The combination of ICE with EE can be performed in different configurations. The first is a series-hybrid, the simplest hybrid configuration, which is also employed for range extender vehicles like the Chevy Volt[4]. In this configuration the ICE is used to supply the battery, which in turn, over the converter powers the EE. A slightly different concept is the parallel-hybrid configuration. In this case both the ICE and the EE are executing mechanical power over the gearbox on the drive axle. This concept allows for a smaller ICE engine, which in turn can

[4]The Volt is not a pure serial hybrid, the ICE delivers direct mechanical power to the axle over a planetary gear in certain driving situations, to increase the overall efficiency (Chambers, 2011).

Table 2.3: Well to wheel primary energy efficiency for the discussed vehicle drive train concepts, numbers according to (Pollet et al., 2012).

Vehicle Type	Well to Tank	Tank to Wheel Components	Well to Wheel
EV	32-100%	Charger 90%, Battery 92% , Inverter 96%, Engine 91%, Mechanical 92% Average Efficiency 66.5%	21.3-66.5%
Hydrogen FCEV	75-100%	FC 51.8%, Inverter 96%, Engine 91%, Mechanical 92% Average Efficiency 41.6%	31.2-41.6%
Hybrid	82.2%	Average Efficiency 30.2%	24.8%
Diesel	88.6%	Average Efficiency 17.8%	15.8%
Gasoline	82.2%	Average Efficiency 15.1%	12.4%

not be employed only to charge the battery while operating at the most efficient conditions.

The battery components of the different hybrid concepts are scaled to enable all electric ranges between 20-60 km. The more energy is charged from the power grid, the larger the battery has to be dimensioned, if no other power source is on board. The onboard generator can be realized in different ways: either the peak power requirements are met by the generator (ICEV or FC) or additional high power components like supercapacitors are added in order to provide peak power, while smaller generators are operated for electricity generation in their efficient operating points (Orecchini and Santiagneli, 2010).

Table 2.3 describes the overall efficiency values of the discussed drive train concepts. The values support the per km consumption values presented in Section 2.6.1. For EVs the primary energy efficiency highly depends on the power source employed for charging. In the "worst" case of 32% overall grid efficiency with thermal power plants and additional transmission and distribution losses accumulate to a well to wheel efficiency ratio of only 21.3%, which is not considerably higher than the overall value of diesel and gasoline vehicles with 15.8% and 12.4% of efficiency respectively. In the best case of employing renewable energy, with a 100% input, still 66.5% are used for mobility purposes. This is an important improvement in comparison to conventional vehicles.

2.6.5 EV Storage Technology

Presently one of the most important parts of EVs and key to the overall technical and economic potential of this technology is the storage component. Electrochemical storage of electricity with batteries has been improved steadily over the

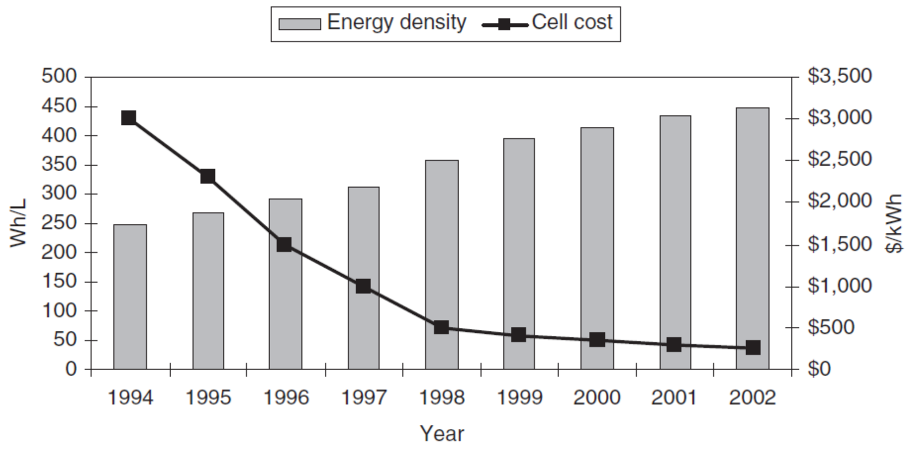


Figure 2.18: Progression of improvements in energy density and cost of standardized consumer "18650" lithium-ion cells (Reddy and Linden, 2011).

last decades. But it was not until 1993 when Sony introduced the Li-Ion Technology for mobile electronic devices, when batteries became more competitive for mobility applications again. Since then the learning and resulting cost reduction effects have supported the development of traction batteries for PHEVs and EV (Reddy and Linden, 2011). Figure 2.18 shows the improvements that have been achieved for the Li-Ion technology on a cell level with respect energy density and cost per kWh. From 1994 to 2002 costs were cut by 90% to 250$/kWh while energy density was increased from 250 Wh/l to 450 Wh/l. This development also helped to support the development of one of the most prominent recent EVs, the Tesla Roadster, which employed exactly 6831 of these cells in its battery pack. The energy density at the battery pack level is still high with 120 Wh/kg and a specific power of 400 W/kg. As we will see later on in this section these values are determining the performance characteristics of EVs.

Before the main technology which prevailed in current EVs, general characteristics of batteries will be described. Batteries are devices that convert the chemical energy contained in their so called "active" materials directly into electric energy by means of an electrochemical redox (oxidation-reduction) reaction (Reddy and Linden, 2011). In these reactions electrons are transferred from one material to another through an electric circuit. This process is more energy efficient and not as limited as other thermal reactions like combustion by the Carnot cycle as it is the case for ICE (and thermal power plants). While we often refer to batteries as the energy storage unit, batteries combine a number of *cells*, which represent the basic electrochemical unit of energy provision. Batteries combine the appropriate number of cells connected in series or parallel according to the voltage and current requirements and also include monitors, controls (or other ancillary components like fuses), terminals, markings and the case containing the cell arrangement. The batteries considered in this thesis are secondary batteries that can be recharged (accumulators), in contrast to primary batteries that can not, or not efficiently be recharged.

Battery cells operate at a given voltage level, for Li-ion cells this value is between 3.7 - 4.2 V (cf. Appendix Table C.1). Connected in series the cells add up to the battery voltage level of the respective application. For EVs the system voltage level is usually higher than 60 V DC, reaching up to 400 V for EE power levels below 100 kW (VDE, 2012). Batteries are characterized by specific indicators, some of the most important ones being: Charge capacity, energy capacity, specific energy, energy density, specific power and number of deep cycles (Larminie and Lowry, 2003). Further parameters, like charge efficiency, self-discharge rates, battery geometry and temperature requirements also need to be considered, but can be aggregated in the overall efficiency of the battery system that is part of the respective EV.

The charge capacity or Amphour (Ah) capacity determines the amount of electric charge that a battery can provide. In particular this means that a Battery with 56 Ah could provide a current of 56 A for one hour, at the specified system voltage. The total amount of energy a battery can deliver depends on the amount of charge and the system voltage. In order to obtain the more common energy storage capacity in Watthours (Wh) we perform the following calculation:

$$E_{Stored} = V_{System} * Ah \ \ [Wh]^5$$

The *specific energy* is the amount of electrical energy that can be stored for every kilogram of cell or battery mass. The values for the cells are higher than for the battery systems as all additional components necessary to form the battery do not increase the storage potential for a given number of cells. The *energy density* is the amount of electrical energy stored per cubic meter of battery volume. For this normally the unit $[\frac{Wh}{m^3}]$ is employed, but as batteries in vehicles are smaller than stationary systems also the unit $[\frac{Wh}{l}]$ is used[6]. The energy density allows for an assessment of storage potential if the approximate value of available volume for the battery is known, and thus has a high impact on vehicle

[5] For a battery system voltage of 380 V we obtain: 380 V * 63.15 Ah = 23,997 Wh, which equals about the 24 kWh storage capacity of the Nissan Leaf. Please observe that 1 Ah equals 3600 C (Coulomb).

[6] $1 \ m^3 = 1000 \ l$

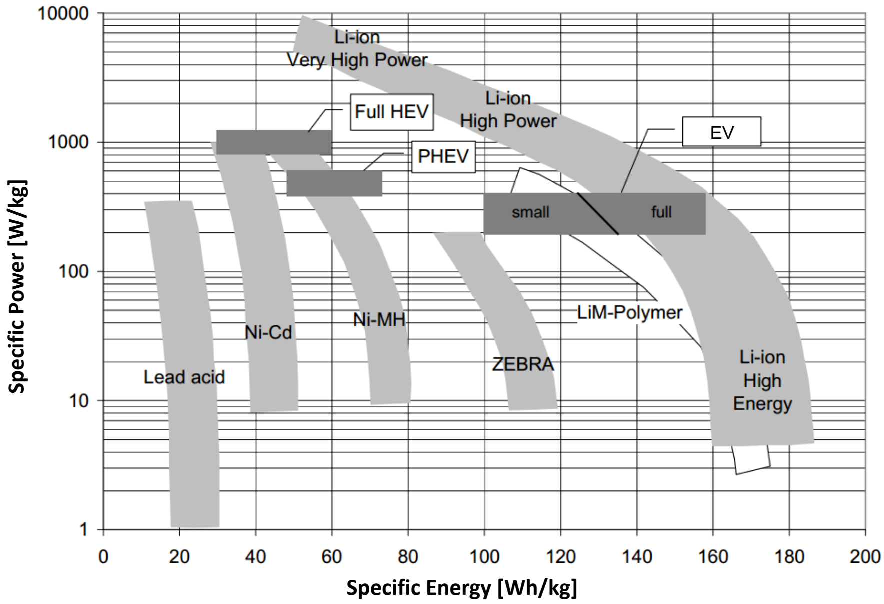


Figure 2.19: Ragone plot for several battery technologies, comparing power and energy density and plotting requirements for EVs, adapted from (Kalhammer et al., 2007).

performance characteristics and design considerations. The *specific power* determines the amount of power per kg of battery. This value is a maximum that should only be imposed on the particular battery for a short time, as otherwise the efficiency decreases and battery lifetime is shortened. The power demand depends on the loads like the EE of the vehicle and the driving energy demand. These situations are usually characterized by dynamic variations in power draw depending on the mode of operation. Battery systems can be designed to support high power requirements and high energy (storage) requirements. Usually high energy batteries can store larger amounts of electricity, but can not supply propulsion systems with peak power, as their specific power values are not as high. In Figure 2.19, a *"Ragone*[7]*"* plot depicts the specific power densities vs. the specific energy for battery chemistries that have been predominantly employed for EVs.

The most common battery type used for vehicles is the lead acid battery. The first electric vehicles were predominantly enabled by this technology, but their rather low specific energy of 20-35 Wh/kg does not permit for an application

[7]A Ragone plot shows the specific energy or energy density of a battery system against the specific power or power density on a log-log scale. This type of graph effectively shows the influence of the discharge load (in this case, power) on the energy that can be delivered by a battery (Reddy and Linden, 2011).

Table 2.4: Comparison of battery performance parameters of main battery chemistries, adapted from (Larminie and Lowry, 2003; Reddy and Linden, 2011).

Battery Technology	Specific Energy [Wh/kg]	Energy Density [Wh/l]	Specific Power [W/kg]	Full Cycles (80% Discharge)
Lead Acid	20-35	54-95	250	800
Ni-MH	65	150	200	1000
Zebra	100	150	150	>1000
Li-ion	90-200	153	300	>2000

in modern EVs (cf. Table 2.4). Nickel cadmium batteries have a higher specific energy and also have a higher lifetime but it was only with the Nickel-metal hydride (Ni-MH) battery, that full hybrids like the Toyota Prius could become competitive and economically viable. Ni-MH has quite a high storage capacity, and is not affected by the so called "memory" effect, as Ni-Cd systems are. The memory effect reduces the capacity of the battery over time, as the capacity is approaching the withdrawn energy amount. Zebra batteries are sodium metal chloride based storage systems, that have a solid electrolyte and operate at high temperatures (320 °C) and have been employed in various EV prototypes, as the performance characteristics are close to Li-ion batteries (DaimlerBenz, 1997).

Because of its favorable characteristics for high energy and high power applications the Li-ion battery is now the most prevalent storage system for mobile applications. Besides the good energy density, Li-ion has a long shelf and cycle life, that can exceed 2000 full 80% cycles, and a lower discharge rate than other systems (Kalhammer et al., 2007). Disadvantages of the Li-ion technology are its moderately high costs, problems with thermal runaway if overcharged or crushed, requiring new procedures for emergency situations. Nevertheless this storage technology still has potential for improvement as different cathode materials are developed that increase energy storage capacity and reduce production costs. Especially Li-air and Li-sulfur based chemistries are expected to increase the specific energy to values well over 400 Wh/kg, more than doubling the performance of current technologies (Gerssen-Gondelach and Faaij, 2012).

As battery systems have a limited lifetime, questions about the sustainability of the application of Li-ion secondary batteries have to be answered. The known lithium resources encompass about 13.7 million metric tons, with about 6 million metric tons as reserves that are accessible considering current technology, (Angerer et al., 2009; USGS, 2013). These resources are mainly concentrated in Chile, China, Australia and Argentina, leaving room for political implications in the future.

Currently only about 25% of the mined lithium is used for battery manufacturing. The most prominent other applications are glass and ceramics production (37%), greases (11%), aluminium melting (7%) and various other applications (25%). The highest increase is expected in the energy storage manufacturing domain, with a focus on traction batteries for EVs. Depending on the prevailing Li-ion battery chemistry, different amounts of lithium per kWh are required, with current values between 150 and 260 g/kWh (Angerer et al., 2009). More important than the main battery chemistry is the demand due to hybridization and electrification of vehicles that is anticipated. When following rather conservative adoption scenarios and a development to about 40% of hybrid and electric vehicles until 2050 in the world-wide vehicle fleet (while considering demand increase for the other application areas accordingly), the available reserves would be depleted to about 59%. If a more radical scenario in which about 90% of the vehicle fleet would be hybrids or EVs, the available reserves would be depleted completely around the year 2045 (Angerer et al., 2009).

These estimates are subject to high uncertainty about future development in lithium processing and demand, but are consistent with most sources in literature which often assume even longer availability of lithium resources. In particular (Andersson and Rade, 2001) assume that lithium will be available well beyond 2100, while already accounting for demand growth in the automotive sector. In any case it is emphasized that recycling of lithium from depleted batteries or other applications is crucial to satisfy demand for a longer time. This in turn means that design considerations must include a recycling possibility already in today's systems. In addition more resource efficient battery technologies must be sought for and alternatives building on more prevalent and thus less costly materials must be developed. Considering the current situation, Li-ion technology seems to be a good first step for electric mobility, with a security of supply for the next four decades. This leaves sufficient time to develop the mentioned alternatives and leverage the experience from the Li-ion development path.

2.6.6 EV Storage Cost Development

Storage costs are key to the development of EVs and their successful application on a large scale. Table 2.5 shows battery costs projections for Ni-MH, Zebra and Li-ion systems adapted from (Kalhammer et al., 2007), for the years 2012-2017. Current estimates support the presented values, (Lunz and Sauer, 2010; Hensley et al., 2012), but suggest that the cost levels are rather on the higher end ranging between 500 - 650 $/kWh or 370-480 €/kWh on the battery pack level.

Table 2.5: Battery cost projections for 2012-2017 considering different scale effects from increased production volumes, based on (Kalhammer et al., 2007).

	Battery Cap. [kWh]	**Module Cost [€/kWh]**	**Battery Cost [€/kWh]**	**Module Cost [€/kWh]**	**Battery Cost [€/kWh]**
Prod. Volume			20,000 Units		100,000 Units
Ni-MH					
EV (Large)	40	237,04	284,44	192,59	231,11
EV (Medium)	25	318,52	**397,78**	259,26	**311,11**
PHEV 40	14	318,52	422,96	259,26	344,44
ZEBRA					
EV (Large)	40	203,70	244,44	148,15	177,78
EV (Medium)	25	203,70	**252,59**	148,15	**183,70**
PHEV 40	14	203,70	270,37	148,15	195,56
Li-Ion					
EV (Large)	40	211,11	253,33	144,44	171,85
EV (Medium)	25	281,48	**351,85**	192,59	**240,74**
PHEV 40	14	281,48	372,59	192,59	256,30

Table 2.5 presents the cost values for the three most common mobile storage technologies, Ni-MH, Zebra and Li-ion under consideration of different scale effects from increased production volumes. The cost values are based on empirical data from manufacturer surveys encompassing expected learning effects and increased production efficiency. It can be seen that an increase from 20,000 produced battery units per year to 100,000 units substantially reduces cost per kWh, e.g. fro Li-ion from 351.85 €/kWh (475 $/kWh[8]) to 240.74€/kWh (325 $/kWh) for the medium sized EV with a capacity of 25 kWh. Batteries are build from basic modules, which in turn contain the cells, thus additional cost for system assembly are taken into account. These additional costs factor about 1.2 to 1.6 times to the module cost. One interesting finding according to (Kalhammer et al., 2007), is that the per kWh cost for PHEVs and HEVs might be higher at the system level, as the power electronics and additional package materials are still required nearly with the same specifications. The absolute costs of the storage system are still lower but only due to the smaller capacity.

The Ni-MH costs for the different battery sizes are in the range of the Li-ion technology, but are not expected to decrease as rapid as Li-ion, as nickel resources are expected to remain scarce. The Zebra battery is the cheapest option, as the main materials in the battery are not as expensive as in the case of Li-ion and Ni-MH. On the other hand Zebra batteries lead to heavier vehicles, which again reduces potential range.

[8] Assuming an exchange rate of 1.35 USD per EUR, the average value for 2007.

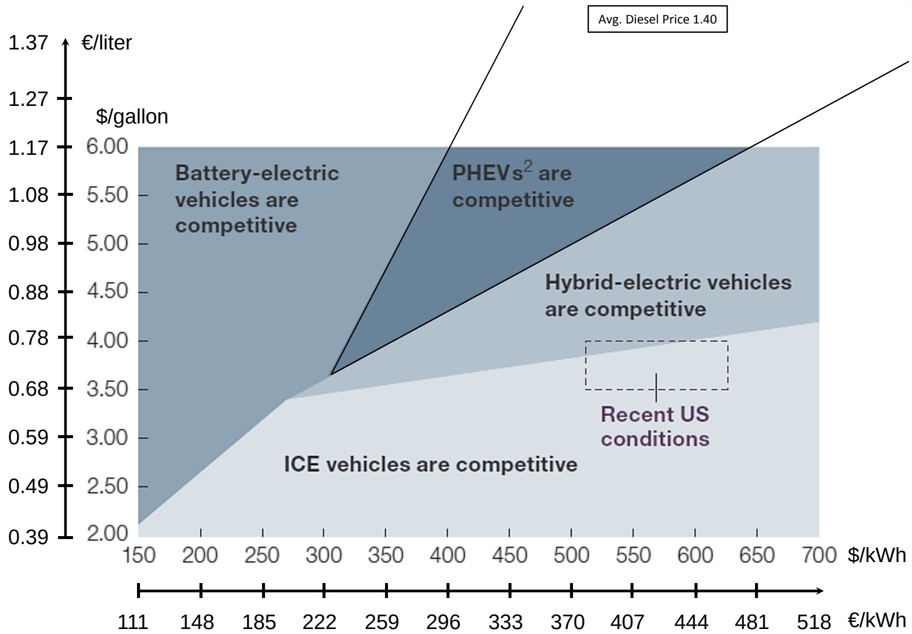


Figure 2.20: Storage cost development and competitiveness comparison of different vehicles types in dependence of recent (2011) fuel prices, adapted from Hensley et al. (2012). Exchange rate is 1.35 USD/EUR for comparability.

Analyses employing total cost of ownership approaches in order to determine at which storage system costs EVs are going to be competitive with conventional or hybridized vehicles suggest that with current battery costs over 370 €/kWh (500 $/kWh) only HEVs are economically viable in the U.S. (cf. Figure 2.20). Under the same TCO assumptions employed in the work of Hensley et al. (2012), building on ANL (2012), Li-ion storage would be competitive in PHEVs in the European, or in particular German context of 2011/12 (depicted by the respective area for the average diesel price in Figure 2.20). Here it must to be mentioned that the investment costs for vehicles are higher in Germany, because of lacking tax credits and the pricing policy of the manufacturers. This pricing policy leads to the fact that similar EVs are priced at the same Euro price as the USD figure, effectively increasing the cost by the exchange rate[9].

As the general adoption of EVs is not as high as expected in most markets without support mechanisms like tax credits, practitioners and OEMs are more hesitant regarding the development of EVs. In addition large new battery manufacturing capacities have been added in the the years 2010-2013 which is likely to

[9]Prius Plug-In Price-Germany: 36,550 €(Toyota, 2013a), Prius Plug-In Price California: 32,000 USD (Toyota, 2013b).

contribute to a price reduction for Li-ion technology in the near future, but will also reduce the number of manufacturers that can continue to operate in spite of high capital costs for the production lines that are not used to their full capacity because of weaker demand. Besides the application only in vehicles new economic opportunities could arise for used EV batteries, that are refurbished and could be used in a stationary setting for grid support, arbitrage or ancillary services. Williams (2012) considered different applications and suggest that most of them are economically viable with current systems as the Chevy Volt battery. Nevertheless some uncertainty about the reliability of Li-ion systems remains, as cycle and calendar life assessment and experience increase only slowly.

2.6.7 EV Grid Connection

EVs need to be connected to the power grid in order to recharge. Grid integration encompasses two main concepts: first to the physical connection of the vehicle with the power grid, and second, the communication and control ability with the respective responsible party for charging coordination. This section is committed to the first part, while Section 2.7 will address the second.

Ever since the first EVs came on the road, the proper connection type and later charge mode are open issues. There have been a variety of different connector types and charging modes that rely on various specifications for voltage and current levels, mostly mapping the requirements of the geographic region the vehicle is operated or manufactured in. In particular the different voltage characteristics of e.g. the U.S. power grid and the European system had an influence on these developments. Charging can be performed either conductive (i.e. using cables and plugs) or inductive (employing an inductive coupling system without physical connection) (Yilmaz and Krein, 2012). As the power grid specifications for both charging methods are similar the focus will be on conductive charging as it is the current standard for EV grid connection.

Charging can be performed in different *modes* and with different *types* of connectors (cf. Figure C.3). In addition there are different power *levels* that are specified for the respective charging modes. Charging modes refer to the specifications and the infrastructure employed for charging. The modes also specify charging currents and therefore for a given system voltage the power that can be used (Van den Bossche, 2010). Charging *levels* refer to specific power levels. This term is also more commonly used in the context of the U.S. power system, where level 1 charging refers to a standard 120 V / 15 A residential socket with 1.8 kW maximum output. Level 2 charging refers to a dedicated infrastructure,

Table 2.6: Overview of charging modes, levels, plugs and their specifications. Values for $cos\phi = 1$. Adapted from (Van den Bossche, 2010; ABB, 2012; Yilmaz and Krein, 2012).

Charging Mode	**Charging Levels**	**Charging Plug**	**Voltage [V]**	**Phases [#]**	**Current [A]**	**Power [kW]**
Mode 1, 3	EU Standard	CEE 7/Type 2	230	1	16	3.7
	EU Semi-Fast	Type 2	230	1	32	7.4
	EU Semi-Fast	Type 2	400	3	16	11.1
	EU Semi-Fast	Type 2	400	3	32	22.2
	EU Fast	Type 2	400	3	63	43.6
Mode 1, 2	US Level 1	Nema 5-20/Type 1	120	1	15	1.8
Mode 2, 3	US Level 2	Type 1	240	1	30	7.2
Mode 4	US Level 3 DC	Type 4/CHAdeMO	50-500	-	100	50
	EU Fast DC	Type 2 Combo	500	-	140-200	70-100

but still in residential or commercial environments with a voltage of 240 V and a current 30 A, providing up to 7.2 kW for charging purposes. Level 3 in turn refers to external charger based DC charging systems.

The charging *modes* are specified as follows: Mode 1 is defined as charging by a non-dedicated outlet with currents up to 16 A, i.e. a standard household socket that has no protective elements special to the vehicle. For residential sockets so called residual current devices (RCD) are in place for most electric installations, providing protections against unwanted leaking currents, but as electricity infrastructure developed over the decades, there is a chance that in older dwellings no appropriate protection is in place (Van den Bossche, 2010). With a proper RCD in place, mode 1 standard socket charging is the most common charging option with powers of 1.8 (US) - 3.7 kW (EU), cf. Table 2.6.

Mode 2 charging mostly refers to a charging connection of the EV to the AC supply network that employs standard sockets, but provides an additional in-cable control box with a control pilot conductor between the electric vehicle and the plug or control box. This mode was primarily designed for application in the U.S., enabling more secure charging at non-dedicated standard outlets. Mode 3 charging involves the direct connection of the EV with the AC network utilizing dedicated EV supply equipment (Van den Bossche, 2010). According to IEC Standard 61851-1[10] a control pilot protection is mandatory for the equipment permanently connected to the grid and the EV. This charging mode enables charging control and allows for a safe charging process that is continuously monitored. Mode 4 is defined as the indirect connection of the EV to the AC grid, uti-

[10] Electric vehicle conductive charging system - Part 1: General requirements.

lizing an off-board charger where the control pilot conductor extends to equipment permanently connected to AC supply. This refers to DC charging systems that are directly connected to the battery system and allow for considerable high charging powers of 50 kW and more, cf. Table 2.6.

The charging power determines the impact the demand of the EV has on the grid. As depicted above in Table 2.6 the available power ranges between 1.8 - 43.6 kW. The EU standard outlets and residential connections allow charging of the EV at rates up to 11.1 kW. Higher powers are restricted to public and dedicated private charging stations with powers from 11.1 - 43.6 AC [11], or 50 kW DC. With the introduction of the Type 2 Combo system charging powers up to 100 kW are possible, but must also be supported by the respective EVs. Charging Coordination is very important if many EVs are clustered in an area or if local and global grid support should be implemented. The ability of the EV to communicate is therefore crucial and must also be enabled by the charging infrastructure. Standard protocols like the ISO 15118[12] are therefore developed and enable the concepts that are further discussed for EV grid integration in the next sections.

2.7 EV Charging Coordination

In order to harvest the demand flexibility of EVs within a DSM program, their charging process needs to be coordinated. The coordination must occur with respect to a given objective. In addition the coordination of demand requirements can be performed within different communication and control architectures. The main architectural concepts are decentralized and centralized control architectures. These categories refer to the level on which the charging decision is made, given an objective and constraints that need to be met given a certain scenario. Figure 2.21 provides a basic classification of the two charging coordination architectures under inclusion of the mixed hierarchical architecture. Following the predominant centralized control paradigms of the traditional power system, centralized charging control architectures build on scheduling procedures that also consider the requirements of the individual charging jobs. These paradigms often rely on planned schedules that are communicated to a central scheduling instance, or assume that a direct load control (DLC) scheme is in place which can be employed to organize the overall charging process such that in particular

[11] For 3-phases power is exemplary calculated as follows: $P = \sqrt{3} * 400V * 63A = 43.6kW$

[12] Road vehicles – Vehicle to grid communication interface (ISO, 2012).

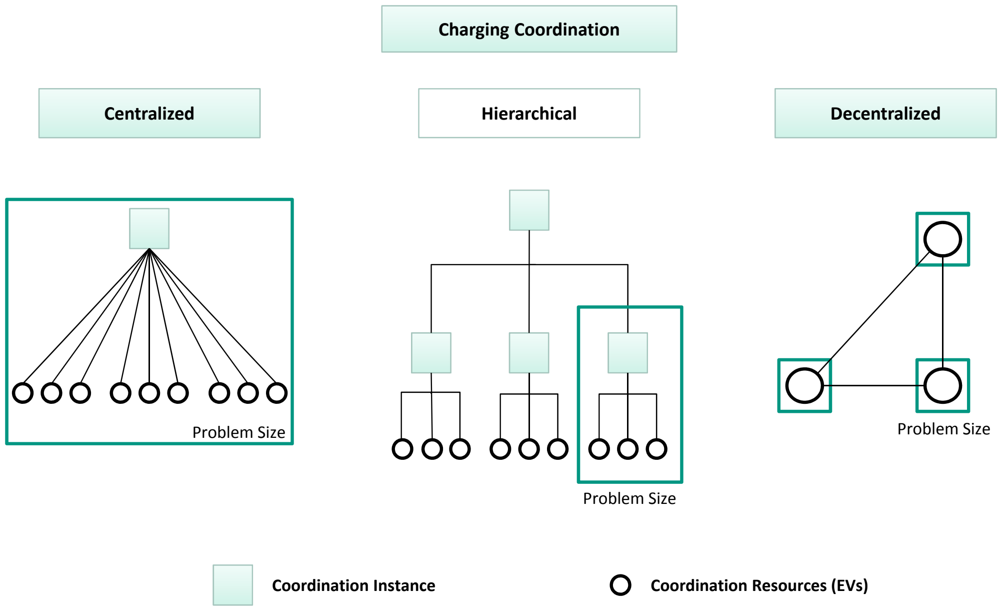


Figure 2.21: EV charging coordination paradigms, adapted from (Malone, 1987).

technical constraints are met. The DSO and TSO are often assumed to be responsible for this form of coordination as technical objectives need to be met for safe and reliable power grid operations (Gonzalez Vaya and Andersson, 2012).

A centralized approach has advantages with respect to reliability of charging control and can be easily integrated into existing power system control paradigms. But centralized control architectures require a high degree of information in order to allow for accurate planning by the central instance. Furthermore central control architectures rely on increasingly complex optimization procedures that do not scale very well in the number of participating units (Li and Shahidehpour, 2005), as with every new vehicle additional constraints are added to the optimization problem. There are many possibilities to reduce the complexity for central coordination procedures or use faster computing algorithms, including heuristics (e.g. genetic algorithms or simulated annealing (Padhy, 2004)) or the division of problems into subsets which can be solved easier. Nevertheless this control paradigm might not be very well received by EV-owners as they do not retain control about the charging process of their vehicle. In order to address the technical complexity and the increasingly more decentralized structure of the power system, hierarchical charging coordination approaches must also be considered.

Hierarchical coordination procedures can be a hybrid form that incorporate aspects of both, centralized and decentralized control paradigms. They can incorporate centralized control and scheduling mechanisms, but in contrast to their system wide counterpart, only address solutions for defined areas or parts of the overall system. This divides the general optimization problem to a set of interconnected but local, and in the best case optimal, solutions. In a more compact setting this traditional approach is thus still applicable from a technological perspective. The drawbacks with respect to the charging decision being delegated away from the EV-owner are still prevalent. In this context the role of a so called aggregator (cf. Chapter 3), an institution that aggregates the load and thus also the load flexibility of numerous EVs in order to participate in the power market, ameliorate distribution congestion (Galus et al., 2011), enhance grid stability through the provision of ancillary services or support the integration of fluctuating renewable energy sources (Caramanis and Foster, 2009b), has been extensively proposed as a hierarchical coordination instance.

Charging control in the hierarchical scenario can either follow a schedule based or a price based coordination approach. In the price based scenario, a price is determined either by the aggregator and communicated to his customer EVs, or it can be determined in a special auction in which the particular EVs participate (Gerding et al., 2011). Price based mechanisms can incorporate the system state, and in particular the regional technological constraints if they are designed accordingly. Following the concept of spot pricing introduced earlier (cf. Section 2.5), prices that reflect local capacity constraints and resource availability enable an efficient resource allocation. Prices can vary by location, a concept following the nodal pricing paradigm or by time, and finally in both dimensions. The hierarchical, price based approach will be one of the two main concepts under investigation in this work.

Decentralized charging coordination builds predominantly on price based mechanisms. Decentralized charging decisions enable vehicle owners or users to decide when and according to which objective to organize the charging process. The coordination mechanism must therefore incorporate the decisions made by the individual EVs in order to allow for an effective and reliable operation of the system while guaranteeing supply for the vehicles. In this category prices can either be determined uniformly for all market participants, or discrimination with respect to location and demand time takes place. Decentralized coordination requires more exchange of information, but the number of necessary parameters that need to be communicated is lower, as the decision problem size is confined to one unit, e.g., one EV.

The different charging coordination architectures can not always be distinguished sharply. Decentral charging decisions based on centrally communicated uniform prices are one example for a mixed form of charging coordination. Hierarchical and decentralized architectures are inherently combined if price signals are calculated on a regional level by an aggregator, while vehicles still make the decision on how to determine their individual charging schedule. The presented classification is thus giving and overview of the general possibilities on how to organize charging coordination. Considering a more abstracted perspective, this classification can be employed for any resource allocation, including other flexible loads. The next sections provide an overview of the most relevant literature with respect to charging coordination of EVs looking into primarily technical and economic objectives and the integration ability of fluctuating renewable energy sources.

2.7.1 Technical Objectives

One of the main areas covered in literature of EV related research is looking into technical questions in particular with a focus on the power grid integration of EVs. Most of the work mentioned in this section also considers economic constraints, but primarily pursues technical objectives under economic restrictions. Scholars investigating the respective questions in the context of the Smart Grid stem from different professions, and provide insights on similar questions from various perspectives. Traditional power systems engineering, as well as electrical engineering and increasingly researchers from computer science and economics investigated some of the following aspects with a technical focus.

One main branch of research is looking into the assessment of EV charging load on the power grid on different voltage levels, with a particular focus on distributions grids. Topics in this domain include the investigation of transformer loads following different charging strategies in given standardized distribution grid structures, mainly with households as an inflexible base load. In this context Optimal Power Flow (OPF) methods play an important role. Other main objectives in this context are peak reduction and load shifting in order to minimize distribution system losses and distribution equipment stress. In addition voltage problems and reactive power provision or compensation in distribution grid settings are investigated.

Analyses with respect to the impact of EVs on distribution system load performed by Lopes et al. (2010) and Mets et al. (2010) show that controlled charging schemes can help to integrate a higher number of EVs in the same distribution system (52 % penetration rate in the coordinated as compared to 10% in the uncontrolled case). In addition peak loads can be significantly reduced by 40 % by coordinated charging. As system peaks are reduced so are losses in the distribution system by around 25% in the analyzed scenarios (Acha et al., 2010). Analyses with respect to optimal charging rates in a residential context show that charging coordination can improve voltage levels and balance phase load in order to reduce transformer equipment wear and integrate higher numbers of EVs, thus deferring costly line and distribution system upgrades, (Richardson et al., 2010; Huang et al., 2012). Most coordinated charging approaches follow the centralized of hierarchical control architecture with rather high information requirements regarding the individual EV-user (Sundstrom and Binding, 2012). Further investigations are looking into the interaction between distribution and transmission systems and thus show that local load situations can be quite different from overall system status and require different integration strategies (Gonzalez Vaya et al., 2012; Salah et al., 2013).

Besides the regional impact assessment there is also work looking into the system wide impacts of EVs. In particular the impact of considerable EV penetration rates on existing power systems and the corresponding unit commitment models in the U.S. are at the center of attention, (Sioshansi et al., 2010; Sioshansi and Denholm, 2010). These analyses are either looking into operational aspects like additional CO2-emissions and costs in the European (Kiviluoma and Meibom, 2011), or U.S. systems caused by the integration of EVs. Other analyses are estimating the reductions in primary energy consumption enabled by EVs and the effects on overall system load (Kintner-Meyer et al., 2007).

Another technical branch of research is focused on the storage and energy feed-back aspect of EVs, known as vehicle-to-grid, (V2G). This notion introduced by Kempton and Letendre (1997) has received a high level of attention. In particular the question if a profitable participation of EV fleets, coordinated by an aggregator, mostly in a direct control scheme has been addressed in different settings. The necessary communication architecture has been assessed in Quinn et al. (2010), the main application domain for V2G is the provision of ancillary services, since regulation and spinning reserve products appear as the economically most stable options under consideration of high battery investment and degradation costs, Tomic and Kempton (2007); Andersson et al. (2010); Galus et al. (2010). In addition energy arbitrage under nodal and wholesale prices in the U.S. and Germany have been investigated (Peterson et al., 2010).

These analyses show in particular that it can be profitable for EVs to provide certain regulation and spinning reserve products, as both the U.S. and the European markets include capacity and energy payments for regulation market participants. Sortomme and El-Sharkawi (2011), Dallinger et al. (2011) also show that the most profitable option to participate in regulation markets is the provision of negative regulation, which means that charging occurs at times when the grid has surplus energy that needs to be withdrawn.

Table 2.7: Characteristic related literature with a predominantly technical focus.

Technical Focus	Main Objective (RQ)	Coordination Approach	Model Scope					Main Finding
Authors			Grid Constraints	Ancillary Services	RES Utilization	EV Trip Modeling	Dynamic Prices	
Acha et al.(2010)	Energy and emission cost minimization through EV grid integration	central	yes	no	(yes)	(yes)	(yes)	Losses are reduced, 30 % EV penetration is no problem, emission reductions are not high due to UK generation mix
Galus et al.(2010)	Evaluate aggregator management model for provision of ancillary services	hierarchical	(yes)	yes	no	(yes)	no	State based short term system operation planing must consider individual trip patterns and resulting energy demand
Galus et al.(2011)	Integrated assessment of EV charge scheduling	hierarchical	yes	no	no	yes	no	integrated planning model and scheduling approach reduces operative peak load from Evs
Gonzáles et al.(2012)	Assesment of EV charging on transmission and distribution level	central /de-central	yes	no	no	(yes)	yes	Local distribution system conditions must be considered for charging coordination
Lopes et al.(2010)	Distribution grid integration of EVs under different charging strategies	central	yes	(yes)	(yes)	no	no	Charging control allows for higher EV numbers, voltage support, loss and peak reduction
Saber et al.(2010)	Unit commitment with EVs using an PSO approach	central	no	yes	no	no	yes	PSO solver can help to successfully integrate large numbers of deterministically available EVs
Sandels et al.(2010)	Assessment of EV aggregation architectures for AS provision	hierarchical	no	yes	no	(yes)	no	Control electronics should be located in EVs, negative regulation is the most cost efficient operation mode
Sortomme et.al.(2011)	Assessment of unidirectional V2G for EVs parked at work	hierarchical	no	yes	yes	(yes)	yes	Unidirectional controlled charging is beneficial for all stakeholders, no additional storage costs
Sundstrom and Binding (2012)	Charging cost minimization under consideration of grid constraints and market bid formulation	hierarchical	yes	no	no	yes	yes	distributed opt. by different roles can support voltage levels, while keeping cost low. High information requirements

This operation strategy incurs no additional battery costs and can be profitable in particular because of the capacity payments that are paid for being available to the power grid at the contracted times. Positive regulation can also be slightly profitable, but needs to consider additional investments in grid and communication infrastructure. In this context is has also been shown that frequency regulation support can be performed by the vehicles (Lopes et al., 2010).

Table 2.7 provides an overview of different approaches in the technical domain. As there are vast amounts of at least partly relevant literature this table provides a general overview of the main areas covered in in EV research with a primarily technological perspective. The table provides an overview of the main research objective addressed, the coordination approach (cf. 2.7) and the scope covered by the model. The categories covered in the scope are the consideration of technological grid constraints (e.g. voltage, power ratings, power flows), consideration of ancillary services, the ability to integrate or support RES utilization. In addition the categories trip modeling of EVs and the application of dynamic prices are taken into account. Finally a short synopsis of the findings is given.

2.7.2 Renewable Energy System Integration

Making EVs more sustainable with respect to green-house-gas (GHG) emissions, reducing fossil fuel dependency and assisting the power grid in the integration of fluctuating renewable generation are some of the core advantages of charging coordination with a focus on higher utilization shares of renewable energy (Richardson, 2013). The literature in this field is often intertwined with economic and technical objectives. Most analyses are focusing on the coupling of EV demand flexibility with intermittent renewable generation. Starting from an overall power system perspective, assessments of EV charging load impacts in systems with a high share of wind-power generation have been conducted, e.g. in Pehnt et al. (2011); Short and Denholm (2006), where the impact of renewable sources (predominantly wind-power) on the merit order of the conventional power plants or the integration ability of additional wind power capacity is assessed. An analysis in the impact for the German case in 2030 was performed by Dallinger and Wietschel (2012). They show that coordinated EV charging, based on a variable pricing scheme and assuming responsive EV-owners can contribute to balance intermittent generation.

Besides a cost assessment in different scenarios, the capability of EVs to reduce system-imbalance e.g. in the UK and Danish system have been analyzed in Druitt and Frueh (2012) and Goeransson et al. (2010). Druitt and Frueh (2012) show that with a wind-power share covering 30% of the UK electricity demand, one million EVs can supply about half of the balancing power required. With higher EV adoption rates of up to 10 million vehicles, about 70-85 % of the balancing requirements can be met only by the vehicle fleet. Goeransson et al. (2010) in turn show that emissions in the danish system can be reduced by PHEVs by a coordinated charging pattern by 4.7% when vehicles have an overall demand share of 20 %. Emission reductions in this case are due to more efficient thermal generation, avoiding additional start ups and part load operation. Addidtional analyses by Ekman (2011) show that coordinated charging and V2G capabilities of 500,000 and 2.5 million vehicles in Denmark are capable to reduce AS and system reserve requirements if wind-power generation covers 50 % of the danish demand. In this case the authors also find that EVs can not provide the necessary demand side flexibility alone, but still need additional controllable generation for back up or other demand side flexibility options in order to reduce the excess wind energy provided.

Other work with a focus on the V2G domain from Kempton and Tomic (2005) shows that EVs can help to provide short term storage in the case of the U.S. power system for up to two hours, but are not capable to serve as a medium term energy storage which allow for a compensation of daily and weekly generation shortages in wind-power production (assuming an installed capacity of 700 GW wind-power and 38 % of the U.S. vehicle fleet being PHEVs that serve as an operating reserve).

Another U.S. case analysis performed by Valentine et al. (2012) for the NY-ISO area shows that coordinated charging according to wind power availability improves system balance, but might slightly improve costs. This study shows that coupling of EV load and wind-power infeed should not be performed in a mandatory but that they should be treated as independent resources in pool markets with unit commitment models. Markel et al. (2009) show that centralized charging coordination with respect to a renewable energy availability signal from the utility can reduce ramp rates for conventional generation by 5 % when a 5% EV adoption rate and 15% RES share of demand is assumed. In addition they show that the communication requirements for centralized fleet control can securely be covered by existing mobile communication infrastructure.

Relevant work with focus on the operative decisions of single actors in a regional setting has been performed e.g. by Finn et al. (2012),Vandael et al. (2011) and Galus and Andersson (2011). Finn et al. (2012) show that in the Irish case DSM measures including EVs can increase the absolute share of utilized wind-power for charging. Vasirani et al. (2011) propose a coalition formation approach to directly map the demand of EVs and the production of wind-generators in a VPP. Galus and Andersson (2011) show that in the region of Zuerich EVs coordinated by an aggregator can help to balance the production forecast error of a 500 MW wind-farm. Vandael et al. (2011) present a hierarchical approach for the reduction of local renewable energy balancing requirements in a distribution network setting. Their analysis shows that while the charging intentions of the individual EVs are still met, imbalances can be reduced by up to 44% as compared to the uncoordinated case.

Table 2.8 provides a short comparative overview of some of the main related analyses. Charging coordination for renewable energy integration has been investigated in different settings, most of the reviewed papers were either focused on balancing fluctuating renewable production, while considering technological and economic constraints. As balancing of renewable energy production must be performed on a short term basis most approaches assume centralized or at least hierarchical control architectures. Balancing occurs for time intervals of 15 minutes, therefore the provision of ancillary services is only partly considered, in particular primary regulation is thus not considered. Besides the assessment of EV demand flexibility employment for RES integration, most approaches also evaluate the changes in demand patterns based on the prevalent market model, or on simple tariffs with respect to the economic impact of the demand shift. Most papers assume that EVs are price responsive and have an automated charging control unit which acts on behalf and according to the preferences of the EV-user. Nevertheless most studies only make basic assumptions about the trip behavior of the vehicles and rather focus on active inclusion of EVs into the power grid. In this respect the work presented in this thesis enhances the existing analyses as real-life driving profiles are employed for the assessment of EV charging demand flexibility with respect to the renewable energy integration potential. In addition this work also builds primarily on decentralized charging decisions, employing dynamic pricing patterns as individual incentives. Thus it expands the perspective of the mostly centralized approaches discussed previously in this section.

Table 2.8: Characteristic related literature with a focus on integration of renewable energy sources.

RES Integration	Main Objective (RQ)	Coordination Approach	Model Scope					Main Finding
Authors			Grid Constraints	Ancillary Services	RES Utilization	EV Trip Modeling	Dynamic Prices	
Druitt et al.(2012)	System wide wind-imbalance reduction through EVs in UK	central	no	yes	yes	(yes)	yes	EVs can reduce balancing requirements for wind-balancing by 50 % while charging costs are lowered
Finn et al.(2012)	Evaluation of DSM-signals for maximum wind power usage while keeping costs low	decentral: scheduling	no	no	yes	(yes)	yes	Cost based minimization strategy promises most benefits in the analyzed case, wind share maximization leads to slightly higher costs
Galus and Andersson (2011)	Balancing of wind generation with large PHEV fleet under consideration of grid topologies.	hierarchical	yes	(yes)	(yes)	yes	(yes)	The MPC model enables the aggregator to balance the wind in-feed error for a 500 MW wind farm
Göransson et al.(2010)	Comparison of different charging strategies in the system of Denmark with respect to total emissions	central	(yes)	no	yes	(yes)	no	Emission reductions in wind-thermal systems are only possible if EVs are actively managed
Kempton and Tomic (2005b)	Assessment of storage options and grid support by EVs	(central)	no	yes	yes	no	no	EVs are well suited for regulation, can be used for peak power, not for medium term storage to compensate for RES shortages
Markel et al.(2009)	Assessment of charging strategies for direct RES utilization	central	no	no	yes	yes	yes	Coordinated charging can reduce peaks, increase RES use, communication infrastructure is sufficient for central control
Mets et al.(2012)	Distributed charging for wind energy utilization	hierarchical	no	no	yes	(yes)	yes	Wind energy utilization can be doubled by the distributed decision mechanism with a hierarchical coordinator
Valentine et al.(2011)	Wind energy balancing and energy price impact of EVs in NY-ISO	central	no	no	yes	(yes)	yes	EVs can support wind integration and contribute to lower prices. Must take wind policy is not cost optimal
Vandael et al. (2011)	Imbalance reduction with EVs, PV case study	decentral: economic	(yes)	no	yes	no	yes	The distributed mechanism could reduce balancing costs by 14-44%

2.7.3 Economic Objectives

The last main group of relevant related work is concerned with the economic evaluation of charging coordination in different market settings and the assessment of allocation mechanisms from an economic perspective. The papers discussed in the following are thus primarily focused on operative economic objectives with some considering technical and renewable energy integration aspects.

Employing the demand flexibility of EVs for the provision of AS was discussed above, one of the main economic assessments for the general viability of the V2G concept was performed in (Kempton and Tomić, 2005b). Based on data from 2003 an economic evaluation of the provision of regulation and spinning reserve products in the CAISO market area shows that EVs, in particular those with a high power connection can generate quite high profits mainly due to capacity payments they receive.

This analysis is quite static and does not consider the dynamics of driving behavior. Work by Andersson et al. (2010) and Dallinger et al. (2011) (both assuming an hierarchical aggregator approach) shows that when the daily variations of prices and mobility patterns are considered, V2G activity is profitable only for certain regulation products. In particular down or negative regulation (in the European context negative secondary and tertiary reserve) can profitably be implemented by EVs.

These analyses show that the capacity payment is a crucial part of the revenue that can be generated by the individual EVs. As mentioned above these approaches consider full availability and control of the participating vehicles. In addition EVs are modeled as price takers, not influencing the price determination of regulation products. Following the analysis of Druitt and Frueh (2012), Quinn et al. (2010) and the sources mentioned above, one can see that the complete capacity requirements for regulation (and thus balancing) can be supplied by less than 10% of the respective vehicle fleets, assuming all of them would be electric, technically capable and willing to participate. V2G can thus be a profitable option for the *first movers* and can even be performed without too high battery degradation costs, (cf. (Peterson et al., 2010)), but will eventually not be a viable option for all EV-owners over time.

Following this observation, the interaction of EVs adjusting their demand (mostly without V2G operations) in accordance with economic signals emitted from the power market is one of the main topics covered in literature. In particular the optimal operation of charging in the U.S. setting within the frame of unit commitment (UC) based pool market models was investigated by Sioshansi

(2012); Caramanis and Foster (2009a); Foster and Caramanis (2013). Sioshansi (2012) compares two operation strategies, one that includes the demand requirements of 1% of the vehicle fleet of the ERCOT service area as PHEVs (~75,000 vehicles) in the ISOs unit commitment model and a tariff based charging strategy for TOU and RTP schemes. The results show that the charging costs in the centralized overall cost minimization UC scheme are lower than in the tariff based scenario. In addition the analysis of the ERCOT case shows that RTP schemes are efficient in communicating the marginal costs of power production to the demand side, but cannot capture the non-convexities of generator start up costs in a system with high shares of coal generation, leading to higher overall charging costs than in the other cases. The work of Caramanis and Foster (2009a) shows that a load aggregator for vehicles can develop efficient charging control strategies for his EV fleet, which allows for successful hedging in the day ahead market but still permits to consider intra-day charging flexibility in the real-time-market. This analysis shows that charging costs can be reduced by at least 20 % as compared to uncontrolled charging, and that EVs can successfully reschedule their demand on a short term basis, under consideration of new information about prices, grid constraints and in particular their own demand requirements. When aggregators consider shorter optimization horizons and grid capacity constraints in their optimization calculus, results from Foster and Caramanis (2013) show that charging costs can be reduced, and the demand flexibility of the vehicles can also be employed in hour ahead energy and regulation products. This shorter charging decision dispatch allows to choose the most appropriate commitment of the available EV demand resources, and shows that accounting for uncertainty in the power system state and the resulting prices needs further investigation in particular in the European (or German) market scenario.

Following the hierarchical and decentralized charging decisions based on day-ahead and spot prices, the following approaches should be mentioned. Rotering and Ilic (2010) are considering PHEVs in the Californian day-ahead market and present optimal smart charging strategies based on dynamic programming, that help to reduce daily energy costs by more than 50 %. In addition they analyze a firm commitment in the regulation market which allows the vehicles to generate additional profits that outweigh the driving energy costs. For another case in which EV owners perform arbitrage accommodation based on the respective LMPs, Peterson et al. (2010), find that when battery degradation costs are considered in V2G operation strategies the annual profit per EV would range between 12-118 USD for historical price data from NYISO, PJM and ISO-New England areas from 2003-2008. This work performs a benchmark analysis and compares the values from a perfect foresight scenario with a naive forecasting technique building on a moving average of two weeks for the respective hours. When uncertainty is accounted for in this manner, the annual profits decrease to values of 6-72 USD. Energy arbitrage is thus only slightly profitable, but could be an option if additional infrastructure for grid interaction would be available to the vehicles, since the analysis builds on the assumption that EVs are not available in the time between 8:00 a.m. - 4:59 p.m., a time that is most likely to incorporate the daily peak prices.

Further Work from Verzijlbergh et al. (2012) compares different charging strategies that are likely to be implemented by different actors and have been described in the related work mentioned before. In particular charging strategies from the perspective of an aggregator, the DSO and a wind-farm operator are considered in the setting of the Dutch power system. The aggregator performs a wholesale cost minimization to satisfy the demand of his customers at a minimum cost level, the DSO in turn distributes load in order to minimize the distribution system losses, and the wind-farm operator employs the charging flexibility to reduce the imbalance between planned and actual production of the wind-generators. In all cases a hierarchical or centralized control paradigm is implemented. The results based on the Dutch case show, that in particular the imbalance reduction strategy highly deviates from the load patterns of the traditional cost minimal and loss minimization approaches. The imbalance strategy leads to highly accentuated peaks in the system that could in turn, if interaction of fleets with differing objectives takes place, increase the overall system balancing costs or create additional stress on distribution system components. Besides the technical comparison a basic cost assessment with respect to wholesale prices shows, that the loss oriented strategy incurs the highest costs. Considering interactions in the respective settings is thus an important aspect for the assessment of charging strategies.

Flath et al. (2013) investigate how decentralized, cost minimizing charging strategies can be improved by the concept of area prices. The study analyzes how different charging strategies perform with respect to average costs and local distribution grid load. Besides the cost minimizing optimal strategy, heuristics that require less price and trip information based on specified price thresholds and a charging strategy incorporating an "*as late as possible*" charging scheme are also assessed. Results show that uniform pricing based on wholesale prices leads to new peaks in the total load of the vehicle fleet, which could lead to overload of distribution assets if the vehicles are regionally clustered.

Table 2.9: Characteristic related literature with an economic focus.

Economic Focus	Main Objective (RQ)	Coordination Approach	Model Scope					Main Finding
Authors			Grid Constraints	Ancillary Services	RES Utilization	EV Trip Modeling	Dynamic Prices	
Andersson et al.(2010)	Economic assessment of EVs for regulation in Sweden and Germany	hierarchical	no	yes	no	(no)	yes	EVs can be profitable for regulation service provision in Germany, mainly due to capacity payments.
Caramanis and Foster (2009)	Cost minimization for aggregator under consideration of day ahead, real time market and grid capacity constraints	hierarchical	yes	(yes)	(no)	no	yes	Rolling horizon optimization enables cost minimal charging for EVs under realistic US market conditions
Flath et al.(2013)	Evaluation of price based charging strategies under different conditions	decentral: economic	yes	no	no	yes	yes	Including locational price components reflecting grid capacity reduces system load and individual cost
Gerding et al. (2011)	Evaluation of a distributed online mechanism for EV charging	decentral: economic	yes	no	no	(yes)	yes	Online mechanism enables efficient distributed coordination with little information requirements
Goebel (2012)	Assessment of economic value of charging coordination for PHEVs	hierarchical	no	no	no	yes	yes	Charging coordination allows for up to 45% reduction of charging costs
Peterson et al.(2010)	Economics of EV energy arbitrage for different LMPs	decentral: economic	(yes)	no	no	yes	yes	Energy arbitrage at given LMP scenarios can be profitable, but overall returns are low given battery degradation
Rotering and Ilic (2010)	Individual cost minimal charging considering ancillary service provision	decentral: economic	no	yes	no	(yes)	yes	Smart charging is beneficial, but ancillary service provision allows for additional profit (no price impact)
Sioshansi (2012)	Comparison of tariff and UC based charging of EVs	central	no	(yes)	no	yes	yes	RTP can lead to higher cost and emissions, DLC performs better in the ERCOT setting

When an additional local price component reflecting the current load of the local transformer is added the load peaks can be reduced by more than 80% while average costs for charging only increase by 15%. This approach thus demonstrates that EVs can be potentially coordinated very well by a dynamic pricing scheme if they are price responsive, rational actors.

Work from (Vandael et al., 2011; Fan, 2012) and (Gerding et al., 2011) emphasizes the decentralized charging decision approach and also evaluates the mechanisms incorporated with respect to their economic or game theoretical properties. Important properties of a mechanism are its incentive compatibility, economic and in particular pareto efficiency, budget-balancedness, individual rationality and strategic robustness, Steinle (2008).

These concepts from the algorithmic-mechanism design domain are important in order to apply distributed decision processes in the critical infrastructure of the Smart Grid. If charging decisions are made in a decentralized manner, mechanisms need to be designed to set incentives for the EVs to participate (rather than not), thus making it individually rational to participate. Incentive compatibility reflects the fact that the information e.g. w.r.t. the demand of the individual vehicle is communicated truthful to the mechanism, making this property one of the most important ones if strategic decision behavior of EVs is considered. Most approaches sketched in the previous section do not assume untruthful behavior of EVs in order to address other explicit questions from the technical domain.

Fan (2012) is investigating a distributed (EV) demand response approach, based on the idea of congestion pricing of communication networks. In particular a discriminatory pricing approach is presented which enables every EV to act according to its individual willingness to pay for the charging rate in a particular time slot. This pricing mechanism is shown to be capable to reduce local load peaks while maintaining computational tractability.

Table 2.9 presents a selective overview of relevant related work with a primary focus on economic assessment or objectives of charging coordination. A considerable part of EV charging coordination literature is concerned with the economic possibilities for the provision of ancillary services by EVs. Most of these V2G approaches employ centralized or at least hierarchical control architectures in order to allow for a reliable provision of the contracted AS-products. Some of them consider uncertainty aspects, or short term dispatch but the main body of literature is considering day-ahead or longer optimization horizons. Further analyses focusing only on the coordinated withdrawal of power from the grid is increasingly build around decentralized, price based decision and optimization mechanisms. These approaches rely on the individual to decide whether or not charging in a particular time frame is aligned with his budget constraints and economic preferences. Technical attributes are mostly considered as constraints in most models, but an explicit economic evaluation with respect to the real time utilization of renewable energy by EVs has not been performed so far.

The literature reviewed in the previous sections showed that EV charging coordination can be categorized in particular with respect to its objectives and its control architecture. In the category with a predominantly technical focus V2G and grid load (regional and system-wide) impacts are the main research area. Work looking into the integration ability of renewable energy sources enabled by EV demand flexibility is in particular focused on reducing imbalances stemming from fluctuating generators, e.g. wind power, on a system and also on regional scales under consideration of grid constraints. Short term storage applications are also discussed, but the coordination of EV demand flexibility by dynamic price incentives is not covered very extensively. Work from the economic domain focuses on the assessment of regulation market participation and day-ahead wholesale market oriented charging. These approaches in turn do not intensively investigate the effect of cost minimizing charging strategies with respect to the utilization of fluctuating renewable energy sources. This thesis is thus focusing on decentralized price based coordination of EV demand for real time integration of renewable energy sources into the power system. The following chapter provides the methodological frame and specifies the research scenario of the analysis.

Chapter 3

Research Scenario and Methodology: Price Based Charging for EVs

3.1 Introduction

Building on the foundations concerning the role and the value of demand response and the possibilities of EV charging coordination in the previous chapters, the following sections will describe the frame and the methods for the analyses performed in this thesis. First the role of the EV aggegrator will be highlighted and the context within in the power market and the power system will be described (cf. Section 3.2). Further on the employed methods, in particular simulation based analysis in the context of power markets and the characteristics of the empirical input data are specified (cf. Section 3.3). Section 3.4 completes the description of the thesis context, as it outlines both, the development of the research questions and subsequent analyses that constitute the basis of Chapters 4 and 5.

3.2 Research Scenario: The Aggregator

Following the description from Section 2.7 and its focus on the active role of EVs in the power system, one of the main control architectures that is employed in the subsequent sections as a basis for the analyses will be addressed in more detail. Since Heydt (1983) and Kempton and Letendre (1997) introduced the notion of EVs as active loads in the power system it became clear that a coordination instance or in particular an intermediary would need to exist in order to bundle or aggregate the technical capacity of a fleet of EVs. This enables their participation in power markets and the respective grid balancing mechanisms. The simple reason for this is that the capacity of one EV (energy and power) is too small to substantially affect system operation or to allow for participation in wholesale markets. Following the idea of the load aggregator (cf. Shahidehpour et al. (2002)), merely an economic interest group that aggregates demand in order to acquire better purchase conditions for electricity, the EV aggregator bundles the technical and economic capacity of geographically concentrated EVs in order to control or set incentives to harness the demand flexibility of the vehicles for grid and economic purposes.

Other definitions of the aggregator role from Quinn et al. (2010) consider "the Aggregator who collects BVs [EVs in order to] create a group to act as [a] distributed energy resource (DER) as the critical entity to make the V2G concept implementable." Further on "the Aggregator also provides [an] interface with the independent system operator or regional transmission organization, i.e. ISO/RTO whose responsibility is to operate and control the bulk power system, and with the energy service providers (ESPs) who provide the electricity supply to customers through the distribution grid." This particular perspective on the aggregator role emphasizes the technical focus. The aggregator is thus considered as "a new player whose role is to collect the BVs by attracting and retaining them so as to result in a MW capacity that can impact beneficially the grid." (Quinn et al., 2010). The definition that will be employed in this work regards the aggregator as an entity that aggregates and satisfies load from regionally concentrated EVs either by buying the respective electricity on the power market or by incentivizing EVs to distribute their load such that a contracted intermittent energy source (i.e. PV and wind-power) is balanced in its generation.

The scenario context for this working definition of the aggregator role is provided in Figure 3.1. The figure depicts the main relevant physical and institutional layers that provide the frame for the analyses following in Chapter 4 and 5. The lower part shows the physical energy delivery layer incorporating the basic voltage level structure of the power system. On the highest voltage level large conventional and renewable capacities are connected, whereas on the medium voltage level more dispersed and smaller generation capacities are connected. The main focus of the following analyses will be on the medium and in particular low voltage level. At this level the bulk demand of households and in particular the corresponding EVs is concentrated. In addition decentralized small scale generators, both controllable and non-controllable are also located on this level. The main questions with respect to the coordination of demand are addressed in this context.

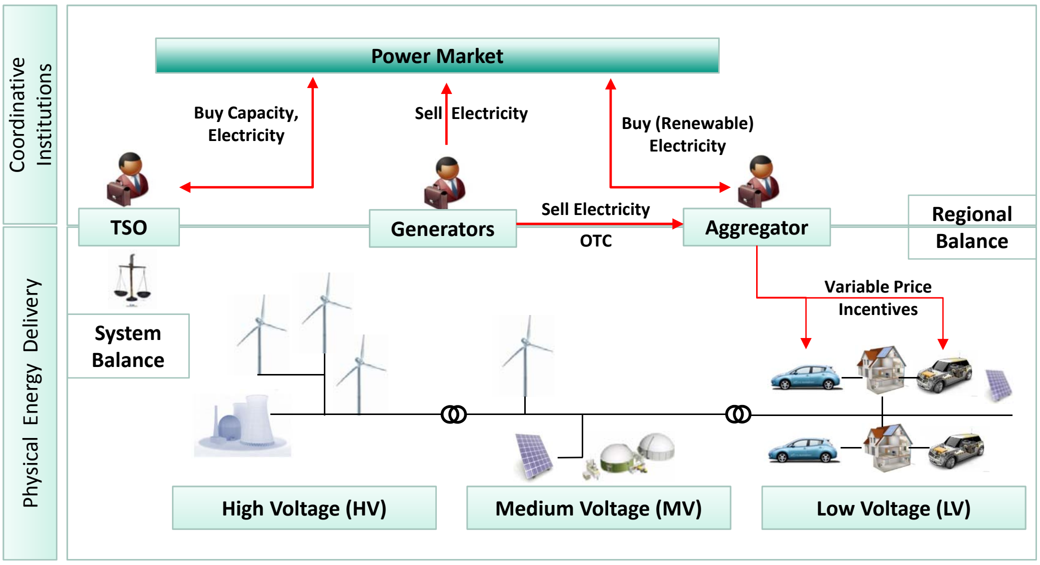


Figure 3.1: General research scenario and main participating roles: EVs coordinated and incentivized by an Aggregator

Above the physical layer, the institutions that organize and provide the frame for the allocation of energy are sketched. Note that the grid architecture and the coordination institutions are not modeled in every detail, but the representation is designed to clarify the relation of the main stakeholders instead. The technical grid balance is provided by the TSO, who needs to be informed about the expected load in a particular region by the responsible balancing authority. Each region can also balance demand and supply on a regional level. This can help to reduce line losses and to reduce the effect of the variability of intermittent generators on the remaining power grid. The aggregator as described above has the main task to supply her EV customers with the energy they request. For this purpose she must buy the electricity on the power market or can contract individual, and in particular renewable generators. The aggregator can also contribute to reduce local imbalances between predominantly intermittent supply and demand by sending the according variable price incentives to his customers. If they respond in a sufficient manner, or in particular respond in such a way as to balance the contracted renewable capacity, the remaining regional system is less destabilized by the given intermittent generation pattern. The absolute effect of course depends on the interaction between the load from EVs, conventional inflexible load, and the overall generation pattern in the given region. In a first step though, it is necessary to assess the demand response potential of EVs on an individual basis. The aggregator thus represents a hierarchical coordination institution that provides (monetary) incentives for her customers to adapt their charging load to achieve the given objective.

Tasks of the Aggregator

The aggregator has several tasks with respect to his customers and the power grid which will be briefly addressed following the work from Bessa and Matos (2012) and Richstein (2011). The detailed tasks will be described in more detail in the respective model context in Chapter 4 and 5. The aggregator needs insight into the demand that he is due to supply. Therefore, forecasting the demand of EVs given certain assumptions about the energy requirements and plug-in times at the grid is necessary. Demand forecasting can be performed on a rather strategic (months to years) or an operative (hours to days) time scale. The focus of this work will be on the latter and will thus assume a given fleet of EVs. Demand of EVs can be difficult to predict as not only the time but also the location of the charging process can vary. Nevertheless, for a given fleet and prominent charging locations like the home of the EV-owner and her work location, a clear demand forecast based on empirical driving profiles can be performed. An individual customer profile that is obtained over time will also improve the forecast accuracy. The data basis that is employed for EV demand modeling in this work is described in detail in Section 3.3.1.

In addition to the demand forecast, the supply forecast for intermittent and variable renewable energy sources like wind-power and PV needs to be provided in order to allow for a coordination of flexible EV demand according to the availability of these sources. Long term forecasts are highly uncertain, but hourly or daily forecasts are well within acceptable error margins of less than 10% of the actual value. Short term forecasts below four to two hours can even undercut the 5% value, (Kalogirou, 2001). The following analyses will assume that renewable generation will be known in order to assess the flexibility potential of the EV demand. Variation is nevertheless accounted for as the analysis time frame is one year which encompasses considerable variation of wind-power and PV outputs.

From an economic perspective an aggregator needs to attract EV-owners in order to take advantage of scale effects and demand diversification when it comes to procurement of electricity. This also encompasses the question which EV-customers need to be attracted. This particular question will not be addressed, instead the characteristics of several sociodemographic groups will be specified, such that a potential aggregator can decide which customers he should attract. Once the customers are acquired the aggregator needs to assess their demand requirements and provide appropriate charging coordination signals in order to influence the load distribution of her customers. The main approach in this work will be a decentralized decision of the EV, given a variable price signal that maps the generation, grid or economic conditions for a defined time span.

Building on the previously specified inputs about demand characteristics, the economic and technical constraints, the aggregator must match the expected demand of his EV customers with the renewable generation capacity he contracted, or acquire electricity on the power market in the respective time slots. In everyday operations the deviations between the forecasted and actual values for generation can be considerable, such as the deviation of EV-demand that e.g. did not respond to the incentives given by the aggregator. This deviation needs to be balanced by other resources in the power system which, in most cases, will lead to additional balancing costs. From an operative portfolio management and risk reduction perspective the goal of the aggregator is thus to reduce these imbalances. This can either be achieved by a more direct control of the EV-load, given that customer energy requirements are always met, or that generation and price responsive demand patterns are better forecasted. In addition the aggregator could also consider to acquire further flexible load types that complement the deviations she needs to address (see above). The demand flexibility potential of EVs to adapt to a given intermittent generation pattern from wind-power and or PV will thus be discussed in more detail in Chapter 5.

It can be observed that an aggregator has a complex set of tasks that she needs to address in dependence of her economic objectives. Naturally not all of these aspects can be covered in this work, but only the aspects related to the demand flexibility potential and its economic evaluation.

The Aggregator Role: Fleet Manager

One of the most prominent aggregator roles that is accounted for in literature is the role of a commercial or business EV-fleet manager (cf. Kempton and Tomić (2005a), Guille and Gross (2009)). This application scenario has the advantage that it substantially reduces the uncertainty about driving energy requirements and recharging times and opportunities. This is due to the fact that the fleet manager knows the trip schedules that are booked for the respective vehicles or even determines the vehicle allocation. EVs in a commercial fleet are likely to have well-known trip patterns and availability times at the power grid, which makes them a prominent candidate for hierarchical or centralized charging coordination mechanisms. Fleets have the advantage that their charging times can be well planned which can be crucial in V2G application scenarios. In addition the distribution of vehicles is contained to a minimum as they are always concentrated in one or several parking lots allocated to the aggregator. This is an additional advantage that requires less infrastructure investments or line upgrades, and depending on the scenario, facilitates the billing of the EV customers. Literature with a predominantly technical focus is thus primarily considering the fleet manager aggregator as a central coordination instance, cf. Table 2.7.

The Aggregator Role: Retail-EV-Customer Aggregation

Another form of an aggregator is the retail customer EV aggregator. This is the primary scenario in the work at hand. This role can be understood as a fleet manager for private EV-owners who delegate charging to an EV aggregator or, in order to maintain their decision flexibility, react to charging coordination signals communicated to them. The main difference to the commercial fleet is the geographical distribution of the vehicles and the private and thus individual ownership of the EVs. The EV-owners that are part of the retail aggregator fleet have a high potential to contribute to demand side flexibility since the potential number of responsive loads is very high at substantial EV adoption rates. The customer basis can be incentivized to change its load pattern within the individual flexibility of every vehicle without a centralized coordination instance, if variable prices are employed as both, incentives, and scarcity signals of available renewable energy. This way every vehicle could optimize for itself, based on private information that does not need to be disclosed to the coordination entity e.g. the retail aggregator. In addition, the potential availability of EVs at the owners home is also higher than in the case of a commercial fleet which is likely to have a greater overall utilization ratio. The distributed decision based on price incentives can achieve higher price sensitivities if automation technology is employed to support the customer charging decision (cf. Table 2.9). Nevertheless this coordination model inherently will need a larger customer basis in order to achieve high participation rates of EV-owners, and thus a reliable balancing of the contracted intermittent generation. A price based evaluation of the demand response potential will thus be investigated in Section 4.2 and in a slightly adapted version in Section 5.3.

The Aggregator Role: Locational Aggregation

The locational aggregator role is comparable to the fleet manager, but can be distinguished by the fact that he does not own or operate the EVs, but merely coordinates their charging process with other demand and supply resources in this region. The region is clearly defined by either the grid topology or a single metering point. Examples for a locational aggregator in a larger urban context, with a clear technical optimization objective (V2G operations) can be found e.g. in Galus and Andersson (2011) and in Section 2.7. The concept of the locational aggregator is thus defined by the technical constraints which have to be considered for the proper integration of EVs into the power grid. The uncertainty about the charging energy requirements in a certain area is not as high as in the retail aggregator scenario, but EVs that regularly, or randomly change their charging location can lead to substantial deviations in the expected energy demand. The temporal assignment of EVs to locational aggregators is imperative from a technological perspective but is at the same time very complex in the legal frame, in particular in Germany, where non-discriminatory access to the individually chosen energy supply company must be guaranteed at publicly installed charging infrastructure, (Pallas et al., 2010). Aggregators that only operate on a private property e.g. a super-market parking lot, can address this issue in a different fashion. In these scenarios customers could purchase power and also decide whether they wish to participate in a charging control scheme or not. Depending on the particular location, the parking time of the vehicles and the travel plans will not allow for any substantial charging flexibility, which in turn will make charging coordination of regularly accessible EVs in the particular area an important mechanism to stabilize and support the local power grid. Section 5.2 will address a locational aggregator concept, assuming full responsiveness of EVs to minimize the deviation between a given fluctuating source and the demand of the EV fleet.

3.3 Methodology - Simulation Based Analysis

Power markets are complex, adaptive systems in which the relation between generation and demand has to be physically balanced at each point in time under the consideration of the transactions and interdependencies between the participants. Analytic methods are not sufficient for an in-depth analysis due to the high complexity. Simulation based analysis in turn can provide insight into the individual, but also in particular the interaction effects of particular roles in the power system under a set of valid assumptions. In addition, through recent developments of computational resources and optimization techniques, simulation allows to model real world systems in an increasingly complex manner. Also simulation based analysis does not require a physical set up and implementation of the research scenario at hand, but can provide valuable insight about how the real world system should be implemented and which interactions occur and - in particular important in this work - which coordination mechanisms should be implemented.

Simulation can be applied to study the features and determining parameters of a system. A system can be defined to be *"a collection of entities, e.g. people or machines that act and interact together toward the accomplishment of some logical end."* (Kelton and Law, 2000). In the work at hand the system is in the widest sense the power system, and in a more narrowed perspective the interaction of EVs as flexible loads that pursue certain objectives like cost minimization or renewable energy utilization.

Systems are characterized by the states that they can have. A state can be defined as the collection of variables necessary to describe a system at a particular time, relative to the objectives of a study. Systems in turn can be discrete or of continuous nature. In discrete systems state variables change instantaneously at separated points in time (e.g. simulation time steps). In continuous systems the state variables change continuously with respect to time, which requires an adequate formal representation (e.g. differential equations). Few systems in everyday life are wholly discrete or wholly continuous, but since one type of change predominates for most systems under study, a classification to one of these classes will be possible (Kelton and Law, 2000).

Systems can either be studied by performing experiments in different relevant set-ups with the actual system, or by experimenting with a model of the system. The latter possibility is the most prominent one, as a physical experiment with the system to be analyzed is often not possible, because it is too disruptive and expensive to do, or even endangers the actual function of the system. Models can also be distinguished by either being of physical nature or a mathematical representation of the studied system or system part. Physical models are scaled or real life models of the analyzed systems. Mathematical models instead, represent a system in terms of logical and quantitative relationships which are altered in experiments in order to determine how the system modeled would react - if the mathematical model is a valid representation.

After a mathematical model has been built it must be examined in order to understand how it can be used to answer the questions of interest about the system

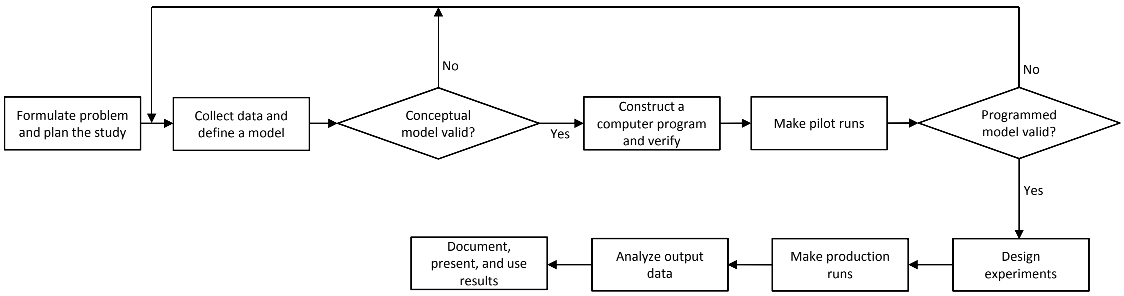


Figure 3.2: Steps in a simulation based analysis, according to Kelton and Law (2000).

it represents (Kelton and Law, 2000). Analytic solutions are exact in describing the causal relationships of a system, but for more complex models they become hard to compute or are even intractable. Given that an analytic solution is not available, complex systems must be studied by employing simulation.

Simulations need to be designed according to the requirements of the studied system and the validity of the obtained solution. Thus decisions about the dynamic properties, the inclusion of uncertainty and the modeling of time in the simulation must be made. A static simulation model maps a system at a particular moment in time, or for which time is not important with respect to the questions posed. A dynamic simulation represents a system as it evolves over time and thus has a trajectory of different states that describe it. If a simulation is deterministic it does not contain any probabilistic (i.e., random) components. In deterministic models the output is determined by the input parameter set, even if the solution is hard to obtain and takes long times to be computed. Many models also require some degree of representation of random or unknown events, which then makes them stochastic simulation models. Stochastic models also lead to at least partly stochastic results or result sets that need to be assessed accordingly. With respect to the representation of time, continuous or discrete simulation are defined as were the respective systems before.

Following the description above, the simulation based analysis in this work is a dynamic, discrete event based deterministic simulation mapping and analyzing the individual objective of EVs and other relevant roles from the power system.

The design of the simulation experiment mainly followed the process described in Figure 3.2: Following the description of current work in Section 2.7

the main problem and the research questions at hand were formulated. The data necessary for the analysis was collected, in particular the driving profiles from the German Mobility Panel (cf.(BMVBS, 2008)), generation and load data of different TSO-control zones in Germany as well as the energy wholesale prices for the respective time period. The first conceptual models focused on the representation of the coordination instance and the sharpening of the relevant parameter set. The first computer programs implemented in Java and employing an open source linear optimization engine analyzed the individual cost reduction potential of EVs, given a variable price (cf. Appendix G for more details). After pilot runs and the validation of the results, additional evaluation scenarios were designed covering different charging strategies. For every part of the analysis the production runs were performed and documented, before the output was analyzed, verified and partly published. Even though the process sketched above contains all relevant steps, further refinements of the simulation tools were implemented in order to allow for the improvement of result quality and analysis processing time during the course of this thesis [1].

Besides the individual simulation based analysis a flexible and dynamic representation of the power system context can be achieved by using Agent Based Computational Economics (ACE) as a method (Weidlich and Veit, 2008). Agent based systems are also increasingly used for the analysis of energy markets in order to depict the relations between the market participants and to analyze events, such as the Californian energy crisis (Sueyoshi and Tadiparthi, 2008), or to examine the economic integration of storage devices (Vytelingum et al., 2010). Individual agents represent the respective participants with their individual preferences, business strategies or goals, and decision processes depending on the particular research question of interest. Formally, an agent is a software system, which at the very least has the properties autonomy, (social) interaction, reactivity, and proactivity (Wooldridge et al., 1995). Despite the already mentioned advantages of agent based systems, their validity has to be critically tested and confirmed with the help of empirical observations and statistical methods in order to be able to draw consistent conclusions (Windrum and Fagiolo, 2007).

In the strict sense of the definition above the simulation based approach in this work is not an agent based simulation, even though individual EVs are modeled that interact to some extent, but in particular react to a given input.

[1] Following Captain Picards advice the repetition of simulation runs in various parameter configurations provided much insight about the nature and the complexity of the problem at hand.

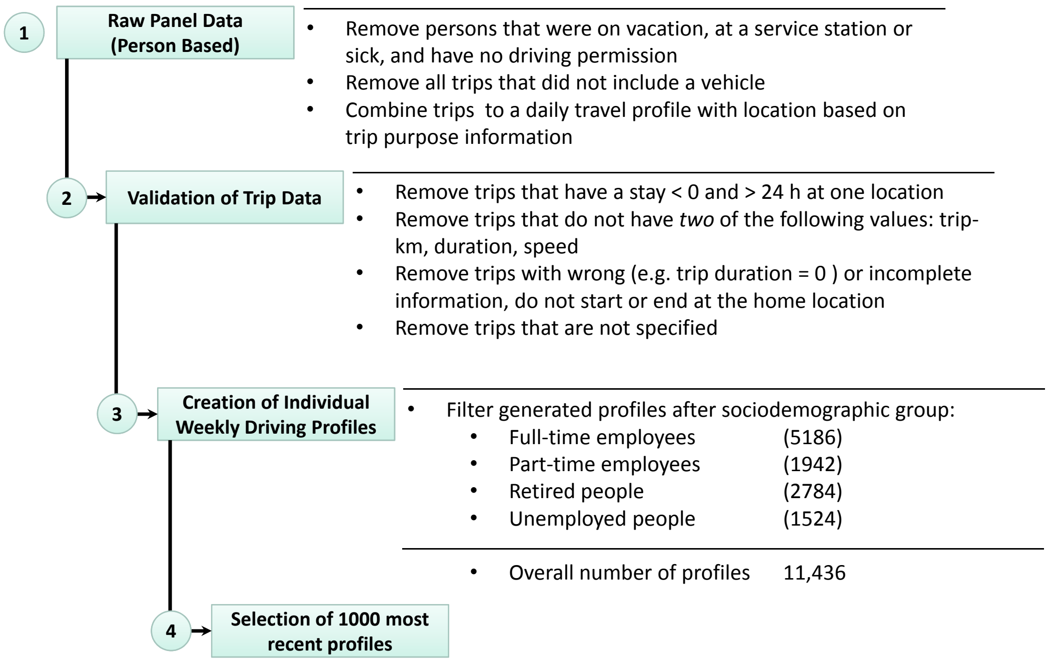


Figure 3.3: Driving profile deduction process based on data from the German Mobility Panel, adapted from (Dietz et al., 2010).

3.3.1 Mobility Pattern Input Data

In order to adequately represent the mobility behavior of German drivers, empirical data from the German Mobility Panel (MOP), (BMVBS, 2008), was employed to deduct valid driving profiles for EVs. Panel participants are randomly selected, but representative households which (self-) report their complete mobility behavior during one week. The weekly data sets are obtained from weeks from September to January, with a majority originating from September to November. This period was chosen in order to have representative data without vacations and other special events such that an approximation for the overall yearly mobility patterns can be obtained.

All trips within the mentioned weekly period are reported, this includes walking and any other form of mobility. In addition the purpose, length, daytime and mean of transport are recorded. The panel data employed was collected between 1994 to 2007, amounting to an overall volume of 530,000 individual trips. This considerable amount of trips needed to be consolidated and filtered in order to obtain individual mobility profiles that can be attributed to a single person and have been performed by using a conventional vehicle. Range restrictions resulting from the use of EVs are considered later in the simulation.

Table 3.1: Summary statistics of the employed mobility profiles.

[km / Week]	Min.	1. Qu.	Median	Mean	CV	3. Qu.	Max.
Employees	1.0	84.0	184.6	225.1	0.76	322.2	956.0
Retired	2.0	48.8	97.5	120.9	0.84	158.5	1034.0
Part-time Employees	1.0	61.4	121.3	159.2	1.31	209.5	1347.0
Unemployed	0.8	34.0	77.2	113.8	1.27	144.2	1993.0

Coefficient of variation: $\frac{\sigma}{\mu}$

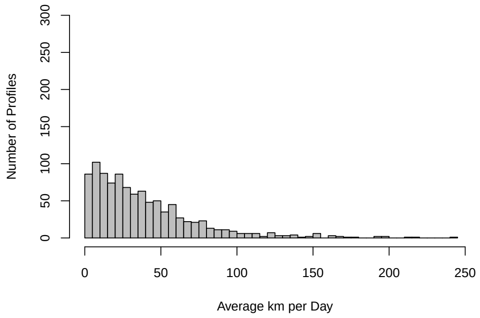
Table 3.2: Relative share of the sociodemographic groups in the Mobility Panel and the German Population of 2007, BMVBS (2008).

	Employees	Part-Time Employees	Retired	Unemployed
Share MOP	40.3%	14.7%	28.0%	8.3%
Share Population	32.5%	11.9%	34.7%	10.3%

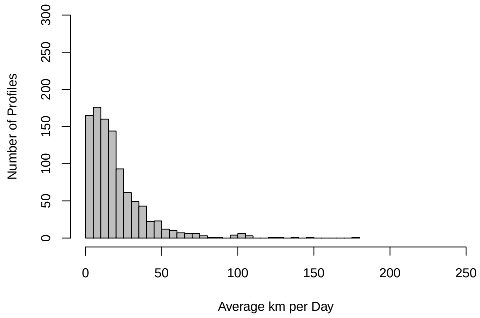
First the trip data was condensed based on *person-IDs* in order to obtain individual driving profiles. In this stage 17,705 weekly profiles of individual persons including only trips with a car can be obtained. Following the general filter process described in Figure 3.3, persons that were on vacation, at a service station or sick and have no valid driving permit were excluded from the data set. The individual trip data was further validated, which included the exclusion of trips that do not return to the home location or have invalid trip lengths and missing values for speed, km and duration.

Further filtering based on sociodemographic criteria and in particular the employment status, leads to a group of 11,436 profiles of which the 1000 most recent for every group were selected for further analyses in this work. The groups are *full-time employees*, *retirees*, *part-time employees* and *unemployed* people, which amount to more than 90% of the profiles in the mobility panel (cf. Table 3.2). When considered as shares of the overall population the two groups of employees and retirees make up 67,2%. In addition these two groups have quite diverse patterns in their mobility behavior, which is why most of the following analysis will only employ these polar sociodemographic groups as a simulation input.

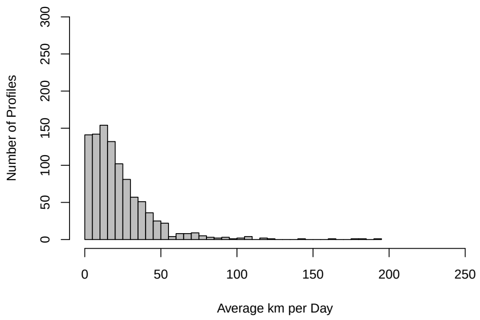
Table 3.1 provides the summary statistics for the employed 4000 driving profiles. It can be observed that the mean driving distance of employees is exceeding the other sociodemographic groups considerably. Also the median for the weekly travel distance is consistently higher with 184.6 km for employees as compared to 97.5 km for retirees. Part-time employees in turn have the second highest travel distances, whereas unemployed people (with some exceptions)



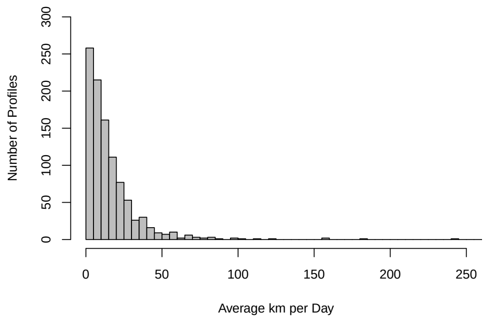
(a) Daily distribution Employees



(b) Daily distribution Retired



(c) Daily distribution Part-time Employees

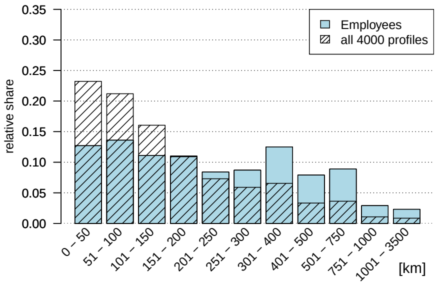


(d) Unemployed

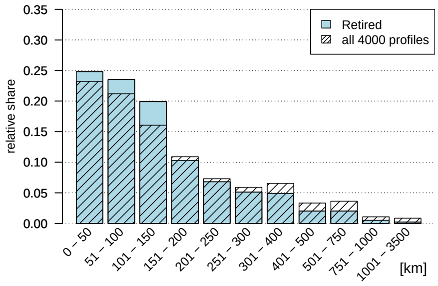
Figure 3.4: Distribution of daily driving distances for the four sociodemographic groups.

have the lowest travel distances. The comparison on a daily basis shows that all groups have the majority of profiles with travel distances less than 50 km per day (cf. Figure 3.4). This is consistent with the observations made earlier in Section 2.6.1 and Table 2.1 and in particular the distribution presented in Figure 2.15. The selection of a subset of driving profiles might weaken the level to which the results can be regarded to be representative for the whole population. But with respect to the major sociodemographic groups the main aspects that characterize a driving pattern (i.e. trip distance and frequency) are clearly addressed by the selected subset.

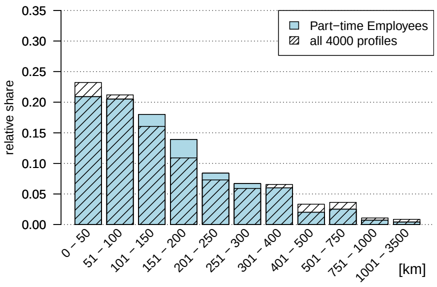
Figure 3.5 depicts a comparison of the weekly driving distance distribution within the four sociodemographic groups. In particular the distribution for every 50 km interval is compared to the value of all 4000 profiles respectively. The comparison shows that employees have a large share of profiles traveling more than 300 km per week as compared to the overall population. Retirees and part-time employees in turn are rather similar to the overall trip distance distribution. The group of unemployed persons is different in the sense that it has a higher



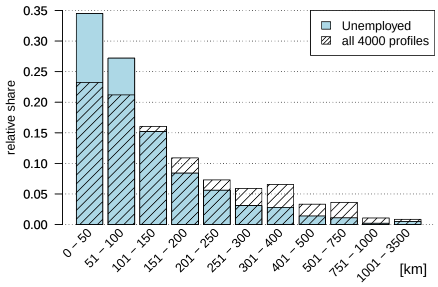
(a) Employees



(b) Retired



(c) Part-time Employees



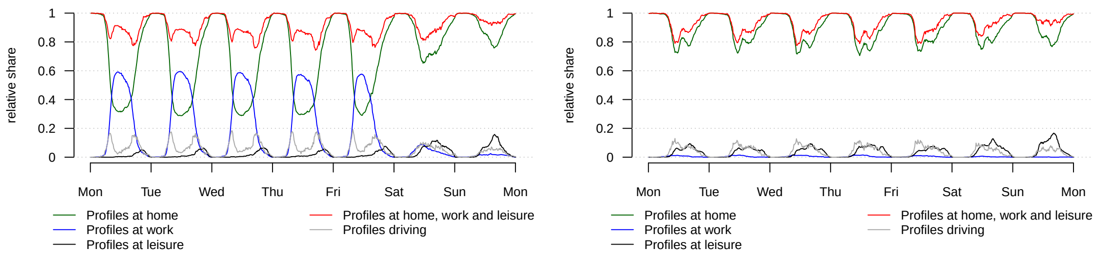
(d) Unemployed

Figure 3.5: Comparison of weekly driving distance distribution of the four sociodemographic groups.

share of low distance profiles. Further individual details of the profile groups will be addressed in the respective sections in Chapter 4 and 5.

The availability of charging equipment at locations that are visited regularly (e.g. work or shopping places) in addition to the home location is an important factor for a reliable operation of EVs. The different generic location types of the vehicles can be derived from the trip purposes recorded in the mobility panel. This enables an assessment of the potential availability for connection times with the power grid and thus provides a frame for the analysis of the temporal demand flexibility of EVs. In Figure 3.6 the availability of EVs at the home, work and leisure locations, as well as the share of EVs that are driving is depicted for employees and retirees over the course of one week.

It can be observed that employees are mainly characterized by the availability at the home and work location. Nearly 60% of the employee EVs are available at the work location during the week. Leisure activities and locations are not that prominent and are concentrated on evenings and in particular the week-end, but in overall less than 20% of the profiles can be found at these locations. What can also be noticed is that no more than 20% of the employees are driving in one



(a) Employees (b) Retired

Figure 3.6: Availability at home, work and leisure locations for employees and retirees over the course of the week.

period at a time. With respect to the availability of employee EVs for the power grid, charging locations at home and work are thus able to cover most demand requirements.

For retirees it can be observed that the difference between the availability at the home location and all other locations is not that substantial. The driving behavior also varies as it is more distributed over the day and less concentrated as in the case of employees. The availability of retirees at the home locations is consistently around 80% or higher at any time of the day, which is a clear indicator for high temporal flexibility regarding charging demand. The absolute demand requirements are not as high as for employees which lowers their potential practical demand response impact. The next subsections will further elaborate on the details of wholesale energy price and generation data employed.

3.3.2 Price Input Data

In order to allow for a realistic economic assessment of the different charging coordination objectives, empirical price data from the German energy wholesale market, the European Energy Exchange (EEX)[2] was collected for 2007 and 2009. The price data includes all hourly reference (i.e. mean) prices of the intraday market of the respective period. Since the simulation employs a 15 minute time resolution the prices during four intervals were set to the corresponding empirical value, adapted by a scaling factor which will be explained in more detail in the respective sections (cf. Sections 4.2.1, 4.3.2). If the optimization objective is not only determined by the economic implications, but by the higher utilization of fluctuating sources, the prices provide the basis to compare the costs resulting

[2] In the meantime European Power Exchange (EPEX): https://www.epexspot.com/en/

Table 3.3: Summary statistics of the employed intraday wholesale energy price time series.

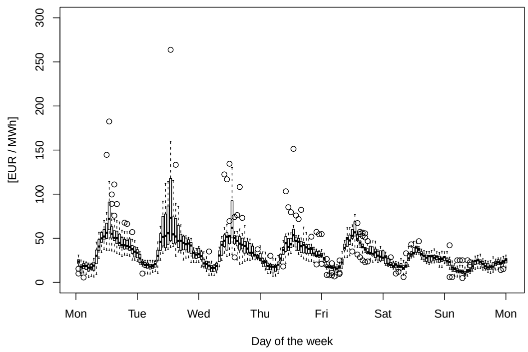
[EUR / MWh]	Min.	1st Qu.	Median	Mean	CV	3rd Qu.	Max.
EEX (2007)	3.69	22.00	31.69	38.21	0.73	46.62	601.10
EEX (2009)	-648.60	28.77	37.86	39.02	0.63	48.34	173.70

from the different strategies.

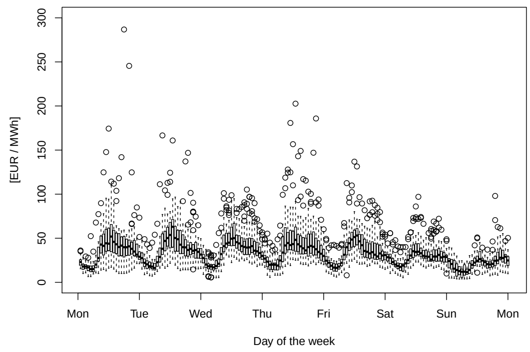
Table 3.3 provides an overview of the descriptive statistics of the empirical price data. One of the main differences between 2007 and 2009 data is the fact that starting from 2008, negative prices were introduced in the market in order to allow for correct economic signals at times of high renewable generation and low load. Negative prices occurred in particular in winter and transition weeks when wind-power contributed a high total share, and load was low due to holidays or week-ends. Due to the grid topology and increasingly problematic transmission grid bottlenecks (Ilg et al., 2012), so called must-run units that locally stabilize the power grid have to bid negative prices in order to be allocated and allow for a secure operation of the power system from a technical perspective. These negative prices provide incentives for flexible demand to shift its consumption and even be compensated for it. For storage devices that operate on an arbitrage strategy this instrument can be very profitable.

The price data was clustered in different data sets based on the TRY (Test Reference Year) climatic day type conditions in order to allow for a better characterization of general patterns in the price levels. The TRY day types are distinguished mainly by the average temperature, leading to three main groups encompassing winter, summer and transition days and are also employed to assess the demand for thermal energy requirements (DWD, 2004). Winter days have an average temperature of less than 5°C, transition days between $5 - 15$°C and summer days above 15°C. This classification enables a better detection of seasonal price patterns that depend on intermittent generation and in particular wind-power.

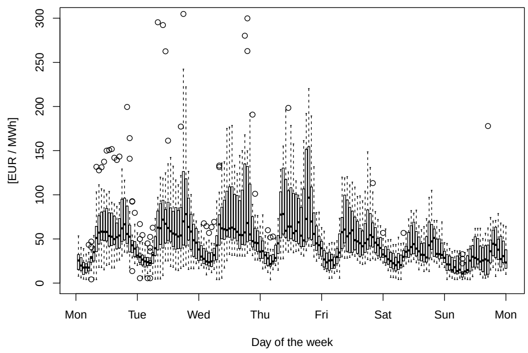
Figure 3.7 shows the price variation for summer, winter and transition weeks for the year 2007. It can be observed, that the variation, and in particular the extreme values, are less prominent in the summer weeks. Transition weeks have more outliers than the other week and day types. Winter weeks in turn have an overall higher price level and the highest range of price variation, often in between 25 - 100 EUR/MWh for the year 2007. In extreme cases the wholesale energy price reached the level of 600 EUR/MWh, a value more than ten times



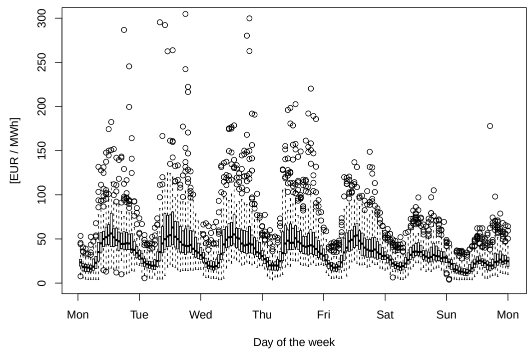
(a) Hourly price variation in summer weeks



(b) Hourly price variation in transition weeks



(c) Hourly price variation in winter weeks

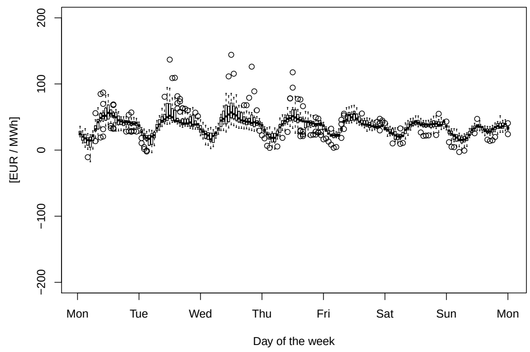


(d) Hourly price variation in all weeks

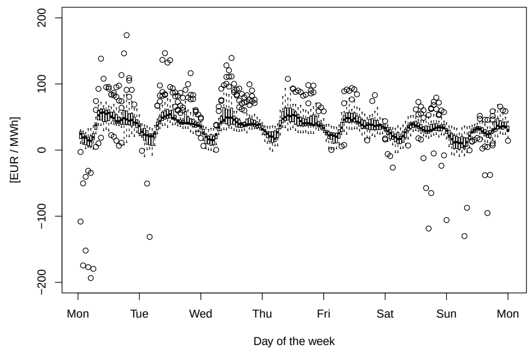
Figure 3.7: Variation of wholesale intraday electricity prices for the year 2007, distinguished by TRY day type, (EEX, 2007).

higher than even expensive hours served by peak generators. When compared to 2009 the overall price level is slightly lower, but the tendency of the outliers is less strong in the positive price direction. Negative prices in turn also reached levels of more than 600 EUR/MWh in 2009, which favors flexible loads that have the possibility to take advantage of these situations.

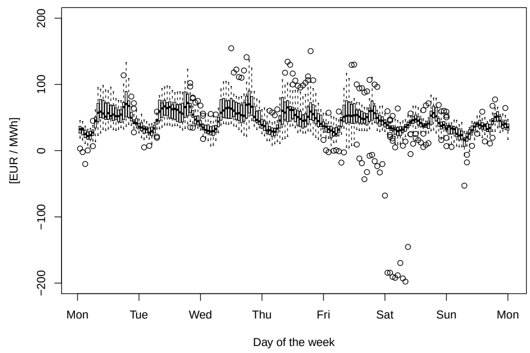
Figure 3.8 shows the different week types for 2009 and the respective hourly price variation. Overall a similar general price pattern can be observed as for 2007, summer weeks have a slightly lower price level, whereas transition weeks have the highest variation and winter weeks have a higher overall price level with a notable variation bandwidth. Negative prices mostly occur on transition and winter weekends which reflects the low load - high wind generation situa-



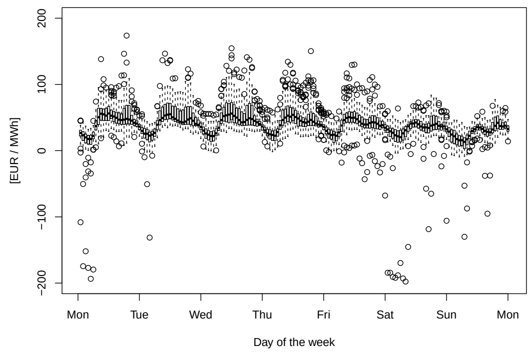
(a) Hourly price variation in summer weeks



(b) Hourly price variation in transition weeks



(c) Hourly price variation in winter weeks



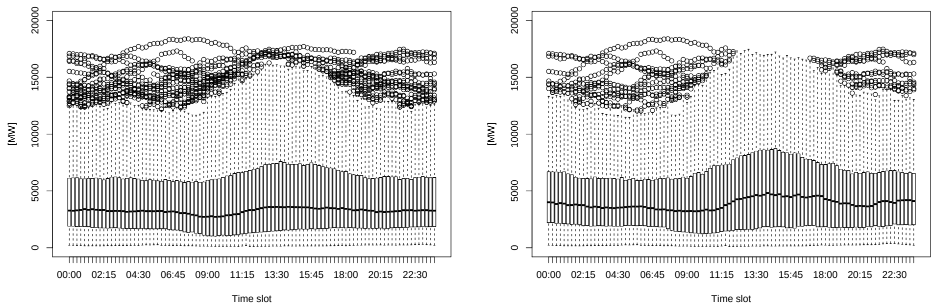
(d) Hourly price variation in all weeks

Figure 3.8: Variation of wholesale intraday electricity prices for the year 2009, distinguished by TRY day type, (EEX, 2009).

tions sketched above. In the analyses performed in Chapters 4 and 5 the prices will partly be scaled to correspond to the end-consumer price level. This procedure has implicit assumptions about the possible dimension of the variable price and the absolute spread which will be addressed in the respective context of the analysis.

3.3.3 Generation Input Data

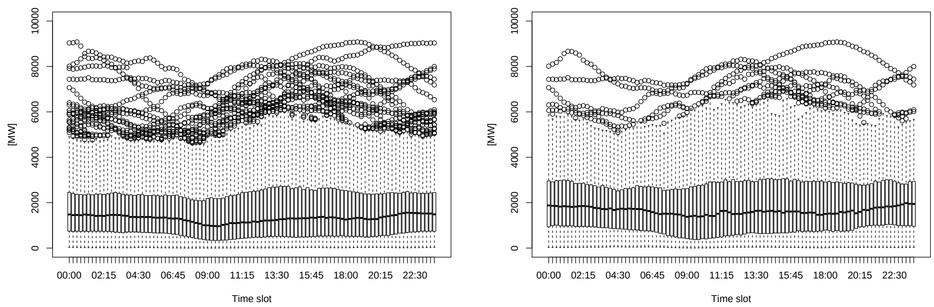
The generation data employed for the analyses covers the wind-power generation time series from Germany in 15 minute resolution for the years 2007 and 2009. In addition PV generation, also in 15 minute resolution, is obtained from



(a) 15 min. wind generation variation for all day types

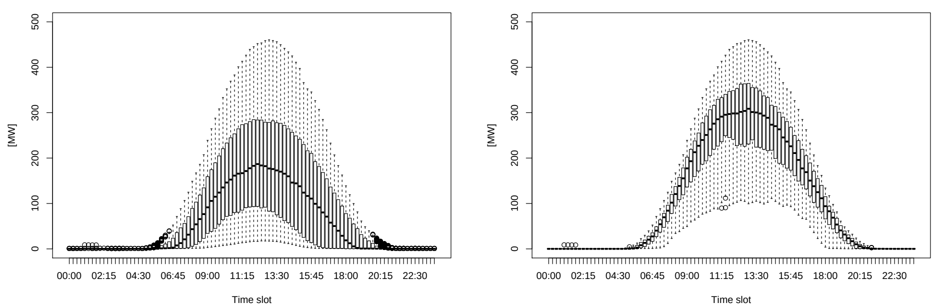
(b) 15 min. wind generation variation for transition days

Figure 3.9: Wind-power generation variation for transitional and all day types for Germany for 2007, (BDEW, 2008).



(a) 15 min. wind generation variation for all day types

(b) 15 min. wind generation variation for transition days



(c) 15 min. PV generation variation for all day types

(d) 15 min. PV generation variation for summer days

Figure 3.10: Wind-power and PV generation variation for different day types from the 50 Hertz TSO-zone, (50-Hertz, 2010).

Table 3.4: Summary statistics of the employed wind and solar generation data for the years 2007 (Germany) and 2009 (50 Hertz TSO-zone).

Gen. Source	Min.	1st Qu.	Median	Mean	CV	3rd Qu.	Max.
Wind (2007), [MW]	113.70	1608.50	3231.20	4513.60	0.86	6386.40	18380.50
Solar (2009), [MW]	0.02	0.29	1.707	59.26	1.57	89.50	460.48
Wind (2009), [MW]	1.24	555.41	1325.57	1788.72	0.91	2430.99	9080.81

the 50 Hertz TSO-zone for 2009. The data serves as empirical input in order to evaluate the integration ability of different charging strategies and the potential for real time utilization of these fluctuating energy sources. The wind generation data sets are different in their regional resolution, as the data of 2007 covers all of Germany, whereas the data for 2009 represents only the eastern part of the country. The data for this part was selected as this region already has a considerable part of variable generation sources as compared to the load that is served in this area. Therefore this can be viewed as a prototype for Germany´s envisioned development.

Table 3.4 provides an overview of the main descriptive measures of the time series employed. It can be observed that wind power has a substantial variation bandwidth, ranging from a minimum of 113.7 MW for the whole country to a maximum of 18380.5 MW in the same year. Most of the time the production is below 6386.4 MW (the 75% quantile) with a mean of 4513.6 MW and a median of 3231.2 MW. The variation can also be observed in Figure 3.9 where the variation on TRY transition days is compared with the overall typical day. The numerous outliers show that a high amount of flexibility is required in the power grid in order to address an ever increasing share of this generation source in the system.

The wind generation pattern is not very clear, the main trend that can be observed is a smaller dip during the morning hours with a following slight increase in the afternoon. But since the variation from the mean can be more than 300% Figure 3.9 can only provide a general impression of the availability of wind-power during a particular day type. The wind generation data of 2009 is similar in its general pattern to the 2007 data, but even less distinctive. Only transition days are similar to 2007, the overall trend is more linear, at least in the aggregate representation. PV generation in turn has very clear diurnal generation patterns (cf. Figure 3.10) that can also vary considerably but are more predictable in their overall behavior. For the following analyses the main characteristics are the relative variation bandwidth of wind and PV generation, since the generation is also scaled in order to assess the possible interaction with a given demand capacity of a fleet of 1000 EVs. The next subsection will sketch the development of the research scenario and the main questions addressed.

3.4 Research Development

Following the notion that in a smart grid environment the flexibility and ability to react to control or price signals will be crucial for system support and the integration of fluctuating renewable energy sources, first research questions arose around the complex of microgrids and virtual power plants and their economic characteristics. In a further specification, economic aspects of flexible loads and in particular EVs in the context of local energy markets were part of first analyses that laid the foundation for the thesis at hand, cf. (Schuller, 2010). Further work that serves as a basis of this thesis developed as follows:

- While focusing on the assessment of individual economic decisions given a variable pricing regime, parts of Chapter 4.2 were presented at the *2012 IEEE Innovative Smart Grid Conference* in Washington, D.C., cf. (Schuller et al., 2012).
- Following an economic assessment of V2G operations strategies of EVs performed in (Dietz et al., 2011) Chapter 4.3 employs a new model including non-linear battery degradation costs, also investigating the economic viability of V2G in the context of the year 2007. This approach is currently under revision at the *IEEE Transactions on Power Systems Journal*, cf. (Schuller et al., 2013).
- In order to consider technical as well as economic aspects of the aggregator role introduced above, a first version of the benchmark model problem formulation was presented at the *2013 IEEE Power Energy Society General Meeting*, cf. (Gottwalt et al., 2013). The model in Chapter 5.2 substantially alters the modeling approach and in particular also considers the impact of shorter optimization time horizons on the ability of an EV fleet to directly match an intermittent generation source with its demand.
- Further work looking into the implications of the supply side employed a uniform pricing approach, following the notion of a price signal that reflects the scarcity of intermittent generation for a given time span. A similar renewable tariff was investigated in (Schuller and Ilg, 2011), but Chapter 5.3 substantially extends this analysis as it considers more complex fleets incorporating the four main sociodemographic groups from the MOP and actual physical generation capacity constraints. Main parts of this chapter were

presented at the *2012 IAEE European Energy Conference*, cf. (Richstein et al., 2012).

The next chapters will address the main research questions from an individual demand perspective and further on from the supply side from the perspective of an EV aggregator.

Chapter 4

Demand Side Assessment

4.1 Introduction

The demand side flexibility potential of EVs is a valuable resource for the power grid in order to integrate a higher share of volatile generation sources and to make the power market more responsive and economically efficient. In order to activate this potential, incentives for EV-owners must be provided such that demand shifting on an individual and decentralized basis can be implemented. A decentralized coordination architecture leaves the decision whether charging actions are altered due to price or other signals to the EV-owner. The following sections will therefore investigate the behavior of economically rational and thus highly price responsive EV-owners that receive a variable pricing scheme (cf. Figure 4.1). This dynamic rate is designed to map the availability of e.g. wind-power in the energy system. Other pricing options are designed to exactly map the volatility of the wholesale power market and thus make the implicit assumption that an EV aggregator will offer his customers dynamic prices, which on average correspond to the recent end-customer level. EV-owners in turn then perform an individual cost minimization for their operative electricity (and later also storage) costs.

The first analysis in Section 4.2 will thus implement a simulation based analysis of individual EV-owners that follow a cost minimization approach, given a variable pricing scheme either based on scaled empirical wholesale power market prices of the year 2007 or the availability of wind power. In addition, further charging strategies that aim to reduce the system peak load impact of EVs are also evaluated in this context.

The second analysis in Section 4.3 adds the important notion of battery degradation costs to the individual cost minimization objective and looks into a more

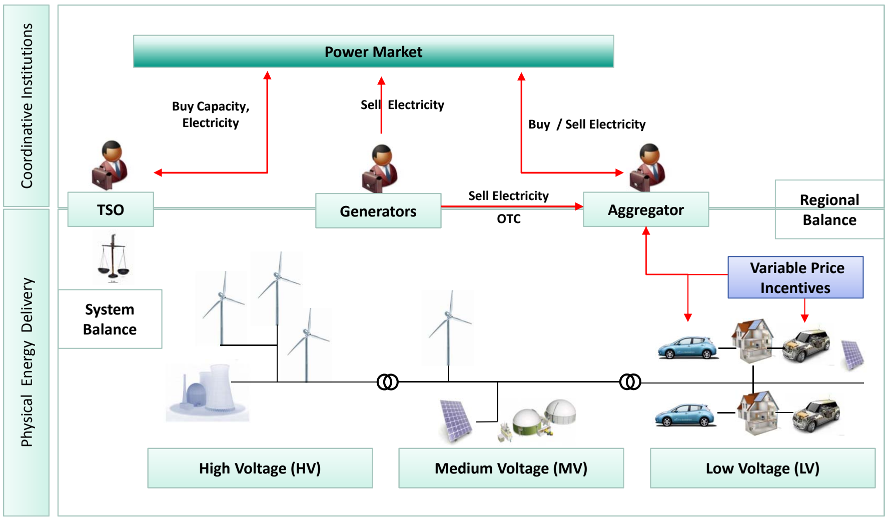


Figure 4.1: Analysis scenario overview for the individual demand side assessment.

active participation of the EVs in the power grid. This in particular incorporates a Vehicle-to-Grid (V2G) charging strategy which transforms the vehicle into a short term energy storage unit that performs temporal energy arbitrage on the power market. For both analyses similar empirical input data for the driving patterns of the EVs and vehicle types are utilized. The same year (2007) is employed as a data basis for the wholesale market price data and the renewable generation and grid load data inputs. This allows for a differentiated comparison of the respective charging strategies and the economic or renewable energy integration implications they invoke.

4.2 Individual Economics: Linear Optimization Model

As sketched above, the demand side in power markets needs to become more active. EVs in particular have a high potential to increase the flexibility of the demand side especially in power systems with high shares of fluctuating generation sources. The interaction of EVs with the power system can therefore benefit both, the power system as it can take advantage of additional flexible loads to increase system stability and the EV-owner to satisfy her individual charging demand with a higher share of renewable energy. This in turn leads to a more sustainable electric mobility as the dependence on fossil fuels is decreased and emissions from conventional power plants are reduced.

In order to realize the demand flexibility potential of EVs different objectives of charging coordination can be pursued. As discussed above in Section 2.6, the main objectives for charging coordination can be technical (e.g. loss minimization, or grid asset protection), emission reduction (e.g. direct utilization or balancing of fluctuating generation) or of economic nature. In this section an economic evaluation of five different charging strategies for individual EVs is therefore performed. This analysis builds on the core assumption that EV-owners react to incentives (or scarcity signals) such that they minimize their individual costs, their impact on the grid or maximize their relative share of wind-power in the electricity charged. In this context, the following research questions are investigated:

RQ 1. - Cost of Individual EV Charging: *What are the individual electricity costs of EVs following an uncoordinated, economically optimized, system load minimal or wind-energy share maximizing strategy?*

RQ 1.1 - Share of Renewable Energy for EV Charging: *Which average share of renewable energy is utilized by a fleet of EVs with real life driving profiles which coordinate their charging according to different economic and technical objectives?*

RQ 1.2 - System Load Factor Evaluation: *What is the resulting load factor for the different strategies and in particular to what extent does charging occur on average during times of low system load?*

In order answer these questions a simulation based analysis with a minimization objective is formulated as a linear optimization program as described in (Schuller et al., 2012) and (Dietz et al., 2011). The main inputs of the model are real life driving profiles of full-time employees and retired people (cf. Section 3.3.1), electricity prices or strict rank orders of other parameters like the load factor, (cf. 4.2.3) based on the yearly data of 2007, and the technical specifications of the BMW Mini E, an exemplary EV with a rather high battery capacity, cf. Table 4.1. The optimization is performed for every vehicle individually and must consider constraints like the guaranteed fulfillment of the respective mobility profile.

This work substantially builds on and extends (Schuller et al., 2012). The following sections will briefly describe the model input data (Section 4.2.1), the formal model and its assumptions (Section 4.2.2), the charging strategies and their objectives (Section 4.2.3), the results of the analyses (Sections 4.2.5 - 4.2.6)

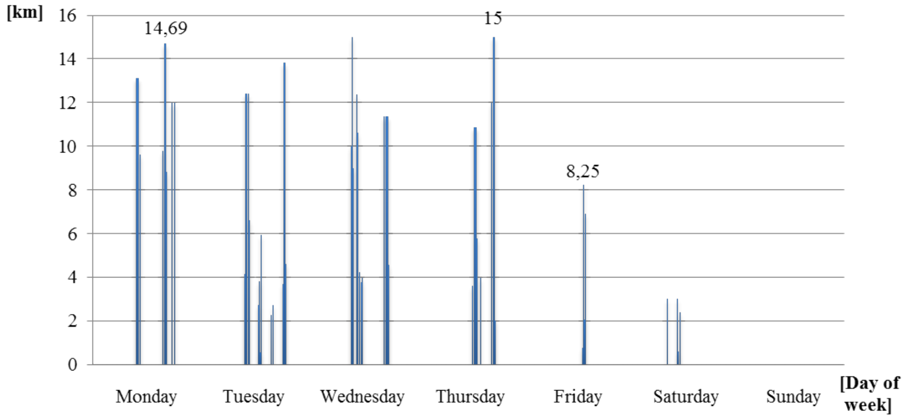


Figure 4.2: Employees: Exemplary driving profile for one week with the respective trip distances.

and the conclusions drawn with respect to the research questions (Section 4.2.7).

4.2.1 Customer Data

The driving profiles employed in the simulation are extracted from more than 11,400 empirical profiles from the German mobility panel, a continuous study of mobility behavior in Germany (1994 - 2007) (BMVBS, 2008), cf. also Chapter 3.3.1. The two modeled groups are full time *employees* and *retired* persons, which represent about 60.5% of the German population of 2007 and around 75% of private vehicle owners (BMVBS, 2008). The driving profiles of panel participants are recorded for one week (cf. Figure 4.2, Section 3.3.1, and Appendix E). In addition to the driving distances, the purpose of the trip is also recorded. Purposes of trips are, among others, trips to work, shopping, leisure or business related locations. This enables the modeling of different charging locations for EVs. In this chapter, the charging infrastructure is only considered to be installed at the EV customers home, which is likely to be the first and less infrastructure intensive step for the introduction of electric mobility.

The profiles of *employees* and *retirees* have an average driving distance of 228.78 km and 119.31 km per Week, respectively. This is a driving distance that can easily be driven with one or two battery charges of the Mini E with an operative battery capacity of 31.5 kWh (cf. Figure 4.3) at the assumed consumption values. When looking at the driving profiles in more detail, it is to be considered that the standard deviation amounts to 180.03 km for employees and 100.23 km for retired EV customers. Nevertheless approx. 90% of the profiles can be fulfilled

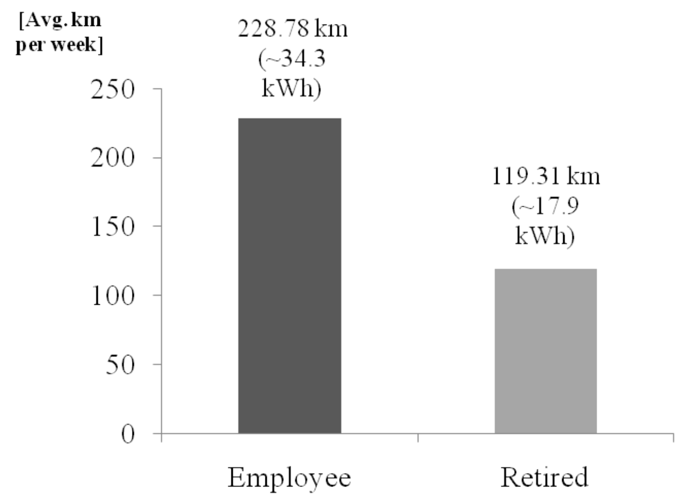


Figure 4.3: Average driving distance and energy demand per week for employees and retirees.

by the Mini E.

Other input data that is employed are the hourly average wind power feed-in of Germany based on 15 minute data from (BDEW, 2008), the hourly total system load for Germany obtained from (ENTSOE, 2007), and EEX intraday hourly spot market prices for 2007 (cf. Section 3.3.2). The prices are scaled to represent the average weighted value of 20.01 ct/kWh in order to reflect the appropriate end-customer price level for this time period, similar to approaches in (Ahlert and van Dinther, 2009; Ahlert, 2010). This scaling is performed in order to obtain a realistic variable price profile. The approach has the implicit assumption that all parts of the end-customer price scale with the same rate and thus could lead to a slight overestimation of the possible electricity price spreads in a variable tariff scheme. This issue is further discussed in Section 4.3 when the EVs are considered as short term storage devices in the German power grid.

4.2.2 Optimization Model

The EV customer is modeled as a cost-minimizing entity which shifts his charging times to the time slots of lower prices or ranks according to the given (price) signal. The model considers the trips as mandatory constraints that have to be fulfilled. This means in particular that if the driving profile is feasible with the specified EV all trips are accounted for. In addition, the maximum driving speed of the vehicle the charging duration and the maximum battery capacity of the ve-

Table 4.1: Technical specifications of the BMW Mini E (BMW, 2009)

Parameter Description	**Value**	**Unit**
Power Consumption	0.14	(kWh/km)
Max Range	250	(km)
Top Speed	152	(km/h)
Maximum C-Rate	$\frac{1}{3}$	(1/h)
Full Charging Time (at 10.5 kW)	3	[h]
Storage Capacity (Usable)	35 (31.5)	(kWh)
Charging Efficiency	93	(%)
Effective Charging Power	10.5	(kW)

hicle are considered. A first version of the model is first defined in (Dietz et al., 2011). The model is extended with respect to the objective function in the following sections. In addition the existing building blocks concerning the battery modeling are described for reasons of completeness.

Assumptions and Parameters

The model builds on the following assumptions about the behavior of the EV customers and the availability of information which is employed for the optimization approach and the time frame of the analysis:

- People continue to use EVs like ICE vehicles.
- Time variable tariffs with hourly changing prices or charging signals are available to EV customers.
- Driving patterns and prices are ex-ante known for one week.
- EVs have an automated charging control device that calculates optimal charging times.
- The fulfillment of the mobility profile is guaranteed, even when charging times are shifted, under consideration of technical constraints.
- EVs are price takers and do not influence prices by their demand.
- EVs can only be charged at the owners home, and are plugged in as soon as they arrive there.
- The battery of the EV has to be fully charged at the beginning and the end of each week (SOC continuity).
- The optimization period is one week.

Table 4.2: Model Parameters

Model Parameter Overview	Symbol	Unit/Domain
Usable capacity of the storage device	C	(kWh)
Min. number of time slots to fully charge	ν^c	(#)
Charging efficiency	η^c	(%)
Storage cost	ψ	(EUR/kWh)
Price per energy unit in time step t	p_t	(EUR/kWh)
Charge parameter for time slot t	φ_t	(%)
Energy consumption in time slot t [a]	d_t	(kWh)
Energy level of the battery at time t	L_t	(kWh)
Rank of hour t	r_t	(1 - 8760)
Location of the EV	z_t	(0: not at home 1: at home)

[a] d_t = kilometers driven in time step t (km) $\cdot$ power consumption per km (kWh/km)

Mathematical Description of Simple Charging

The first and most straight forward charging strategy is *Simple or (as further denoted) As Fast As Possible (AFAP) Charging*. This strategy does not consider external factors, but only the demand implied by the driven distance and specific energy consumption. The strategy thus recharges whenever this is possible (e.g. the vehicle is at the home charging location) and can be formalized as follows:

$$\varphi_t = \begin{cases} 1 & : \text{if } SOC_t + \frac{C}{\nu^c} \leq C \text{ and } z_t = 1 \\ \frac{C - SOC_t}{\frac{C}{\nu^c}} & : \text{if } SOC_t + \frac{C}{\nu^c} > C \text{ and } z_t = 1 \\ 0 & : \text{otherwise} \end{cases} \tag{4.1}$$

The costs resulting from this charging strategy are described as follows:

$$Cost = \sum_{t=1}^{T} \underbrace{p_t \cdot \frac{C}{\nu^c \cdot \eta^c} \cdot \varphi_t}_{Electricity\ \ Costs} + \underbrace{\frac{C}{\nu^c} \cdot \psi \cdot \varphi_t}_{Battery\ \ Usage\ \ Costs} \tag{4.2}$$

$$Cost = \sum_{t=1}^{T} \underbrace{p_t \cdot \frac{C}{\nu^c \cdot \eta^c} \cdot \varphi_t}_{Electricity\ \ Costs} \tag{4.3}$$

The first term in the cost function in Equation 4.2 is due to the variable costs that are incurred for the purchase of (driving) electricity. The second term represents the costs due to the usage of the battery storage. For the following analysis storage costs that are due to the energy throughput in the battery are not considered in the comparison of the operative costs between the different charging strategies, as the energy amount is equivalent for all charging strategies in the presented problem formulation. Thus the storage costs do not affect the operative and in particular electricity purchase costs, since they are similar for all strategies (cf. Equation 4.3). The battery usage costs do vary between sociodemographic groups. Section 4.2.7 will discuss the resulting weekly costs for different battery cost levels. In addition Section 4.3 will investigate the role of battery degradation costs related to energy throughput and charging power in more detail. The goals of this section is to provide insight on the individual operational costs of different charging strategies that will be described in more detail in the next paragraph.

Objective Function Smart Charging (SC)

The objective function of Smart Charging is to minimize the costs incurred, given a price for each time step of the optimization horizon of one week.

$$\min_{\varphi} \rightarrow Cost = \sum_{t=1}^{T} \underbrace{p_t \cdot \frac{C}{\nu^c \cdot \eta^c} \cdot \varphi_t}_{Electricity\ \ Costs} \tag{4.4}$$

The term in the objective function corresponds to the operative formalization of AFAP charging, but this time the objective function value is minimized. When Smart Charging is compared with AFAP charging, the battery usage term can be neglected without loss of generality, as the storage cost and the total energy amount are the same for both strategies, assuming linear battery costs. The only deviation between the strategies thus occurs for the energy costs. This difference is caused by the shifting of charging times in the Smart Charging scheme. Other costs, like investment costs for the vehicle, are not considered in this approach since the focus is on operative decisions. Following the objective function the constraints in the following paragraph also apply.

Constraints

Equation 4.5 states that the SOC of the battery can not be higher than the actual capacity C and not lower than zero. The SOC is equal to the SOC in the previous time slot plus the amount of energy that has been charged into the battery minus the energy discharged for driving purposes. Equation 4.7 states that the amount of energy charged into the battery is equal to the demand during the simulation period. This also implies that the battery is fully charged at the beginning and end of each week in the analysis.

$$C \geq \underbrace{L_{t-1} + \frac{C}{\nu^c} \cdot \varphi_t - d_t}_{SOC_t} \geq 0,\ \forall t \in [2, T] \tag{4.5}$$

$$C \geq \underbrace{L_1 + \frac{C}{\nu^c} \cdot \varphi_1 - d_1}_{SOC_1} \geq 0,\ t = 1 \tag{4.6}$$

$$\sum_{t=1}^{T} \frac{C}{\nu^c} \cdot \varphi_t = \sum_{t=1}^{T} d_t,\ \forall t \in [1, T] \tag{4.7}$$

$$p_t, r_t, d_t, C, \eta^c, \nu^c, \psi \geq 0,\ \forall t \in [1, T] \tag{4.8}$$

$$\varphi_t \in [0,1] \text{ and } \varphi_t \leq z_t,\ \forall t \in [1, T] \tag{4.9}$$

$$z_t = \begin{cases} 1 & : \text{EV at home within time step } t \\ 0 & : \text{otherwise} \end{cases} \tag{4.10}$$

$$t \in [1, T] \tag{4.11}$$

The simulation period is one week with T being 672 time slots, one time slot for every 15 minutes in one week. The analysis time frame is one year, consisting of 52 weeks and a total of 364 days, with data from 2007.

4.2.3 Charging Strategies

In the following section, five distinct charging strategies are assessed with respect to their individual economic implications. The strategies are:

- *AFAP* charging which serves as a benchmark for uncoordinated charging since it only seeks to recharge whenever possible in order to maximize the available driving range. *AFAP* does not consider the system status, renewable energy availability or electricity prices for its charging decisions.

- *Smart Charging (SC)* initially minimizes the individual payment of the vehicle given the variable hourly prices based on the EEX-spot prices of 2007 (cf. Equation 4.4). This strategy is further denoted as *EEX* and serves as the best case benchmark of the individual costs incurred.

- *SC* with the objective to maximize the relative wind power share for each time step t used for charging. This strategy shifts charging to time slots of the highest relative availability of renewable energy, in particular wind power, and is further denoted as *WL, (wind-load)*. The formal objective of this strategy is thus to maximize charging during time slots in which the following ratio has the highest values:

$$\frac{P_{Wind_t}}{P_{Load_t}} \quad \forall t \in [1, T] \tag{4.12}$$

- *SC* with the objective to minimize the system load factor in each hour t in which charging occurs is denoted as *LF*. This strategy shifts EV demand distinctively to times with the lowest overall system load factor, thus corresponding to the well known night or off-peak charging strategy often mentioned in related literature. The strategy seeks to minimize its average system load factor, and thus shifts charging to time slots in which the following ratio has the lowest values within the optimization horizon:

$$\frac{P_{Load_t}}{max\ P_{Load_{2007}}} \quad \forall t \in [1, T] \tag{4.13}$$

- *SC* minimizing the system impact while balancing for renewable energy generation in the optimization period. Following the concept of the residual load, the *Residual* charging strategy has the objective to charge the EV whenever the residual load in the optimization period is the lowest. The residual load is defined as the total system load subtracted by the amount of variable and uncontrollable generation. The residual load is therefore the "*net*" load of the system that has to be covered by (conventional) controllable sources. This charging strategy thus provides a signal for EVs to charge only at a low overall load situation, or at times in which renewable, and in particular wind, generation provides a high share of total load. This strategy minimizes the following term for the charging time slots selected:

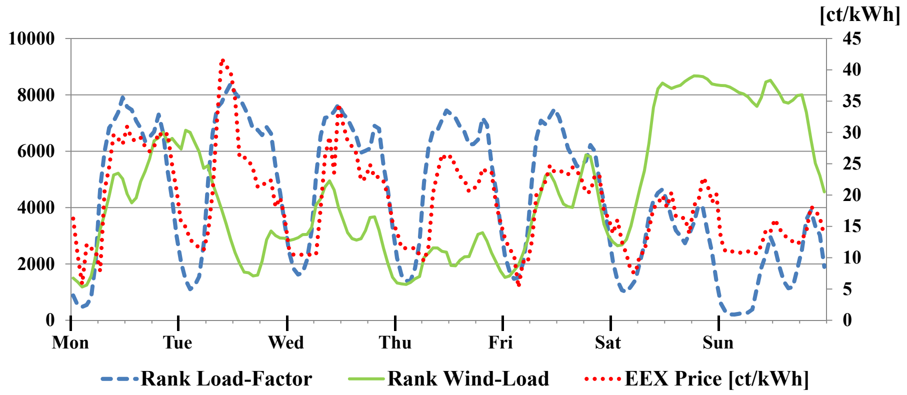


Figure 4.4: Rank of Wind-Load and Load Factor (both dimensionless) in comparison to the scaled EEX-price for week 37 which is further consistently employed for explanations.

$$\frac{P_{Load_t} - P_{Wind_t}}{max\ P_{Load_{2007}}} \quad \forall t \in [1, T] \tag{4.14}$$

AFAP and *EEX* charging are implemented following Equation 4.2 and the objective function formulated in Equation 4.4. In order to coordinate EV charging according to the objectives of *WL*, *LF* and *Residual*, the objective function has to be adapted accordingly. The next paragraph introduces the rank concept which provides a possibility to set the required signals for EV charging coordination.

Rank Concept

A strict ascending order is created for all hours of 2007 with respect to wind power availability, load factor and residual load situation (cf. terms 4.12, 4.13 and 4.14). For *WL*, this implies that for hours with a relative high wind power availability the absolute rank assigned is low, which provides a signal for the EV to maximize the wind power share utilized for charging. The same rank mapping procedure is also applied for the relative load factor and the related residual load concept for every hour in the investigated period. The hourly ranks are then assigned to each 15 min. time step t of the respective hour. This leaves the linear optimization some room with respect to the explicit time slot it determines for charging and enables a consistent economic evaluation, since the variable tariff based on the EEX price also has a hourly resolution.

The variation of the hourly ranks and the EEX oriented hourly tariff are exemplary depicted for one week in Figure 4.4. The single days can clearly be differentiated in the *EEX* (mapped on the secondary axis) and *LF* regime (mapped on the primary axis). It can be observed that for the depicted week the availability of wind power on the weekend is rather low, expressed by higher ranks for the respective hours, whereas in the middle of the week a relatively high share of wind power with the respective lower ranks is available. This availability or scarcity signal guides the objective of the individual linear optimization.

Objective Function Rank Smart Charging

$$\min_{\varphi} \rightarrow RankSum = \sum_{t=1}^{T} \underbrace{r_t \cdot \frac{C}{\nu^c \cdot \eta^c} \cdot \varphi_t}_{i} \tag{4.15}$$

The adaptation of the objective function employing the rank concept is based on the replacement of the respective price p_t by the corresponding rank r_t as assigned for each t by the process described above. Thus, the new objective function can be reduced to the minimization of the weighted rank sum which is determined by the rank factor. The equation is thus similar to the cost minimization objective, but determined by the rank and thus the relative quality of the time slots chosen for charging. The economic evaluation of rank charging schedules is performed on the same basis as for the *AFAP* and *EEX* strategies. This allows to assess the individual cost implications of the respective strategies. Further implicit assumptions and a more detailed discussion of this evaluation method are provided in Section 4.2.5.

The rank concept has the advantage that it can easily be mapped to a tariff structure according to the individual revenue plan and situation of any EV aggregator and thus also provides insight for the supply side on how EV-owners can distributed their load based on the respective charging rate or signal.

The customer model in this chapter is only looking for the existing minima but does not consider the absolute price level of a tariff scheme, as EV customers are very likely to do in reality. Considering the assumed perfect foresight of the relevant information for the optimization, the results that are presented in the following section can be regarded as a best case benchmark for the described simulation scenarios.

4.2.4 Scenario Setup

The simulation scenarios map five different charging schemes: *AFAP* charging, *EEX* charging, load-factor oriented charging *(LF)*, wind-load ratio *(WL)* and residual load (*Residual*) oriented charging. The optimization is computed for each of the 1000 profiles of *employees* and *retired* EV-customers, for all weeks of the year 2007. Some profiles are not feasible with the Mini E, in particular if the charging time required for the respective trips is too short to charge enough energy for the next trip or the trip distance is too long for the specified maximum range of the vehicle. Such profiles are excluded from the following analysis in order to have a consistent data basis. Nevertheless, for *employees* still 89.3% and for retired EV-owners 93.7% of the profiles are feasible.

All charging strategies are evaluated according to the research questions formulated above. This permits for a comparison in terms of economic aspects, grid stability, or near "real-time" green power utilization rates. In order to enable an economic comparison of the different charging strategies EV demand under the *LF*, *WL* and *Residual* optimization strategies are assessed according to the corresponding EEX price of the respective charging time slots. Thus the different strategies can be compared in economic terms on the same basis.

4.2.5 Results Employees

The results of the simulation for the *employees* are summarized in Table 4.3. With respect to the relative share of renewable energy incorporated in the charging demand (RQ 1), it can be observed that *AFAP* shows only about half of the utilization rate of wind power as compared to *WL*. In fact the utilization ratio is lowest for *AFAP*. *WL* in turn has an average utilization rate of 14.72% while it shifts charging to periods with an average load of 62.01% (RQ 1.1). The *EEX* strategy charges at an average wind share of 11.02% which is more or less in the middle between *AFAP* and *WL*. *Residual* in turn is slightly more sustainable in this respect than *EEX* as it has an average wind-power share of 11.89% during its charging times.

EEX shifts charging to periods of lower load with an average load factor of 57.13% which is in between the optimal *LF* and the *WL* strategy. The load factor for *WL*-charging is still considerably lower as in the *AFAP* case but shows that the availability of wind power and the driving profile restrictions have an impact on the system compliance of this strategy. *AFAP* charging again is the worst performing strategy with respect to the system load impact, with an average load factor of 77.89%.

The *Residual* charging strategy resembles the *LF* strategy, as it also charges at low overall load situations while it still considers the availability of wind power. In particular, this strategy performs charging when the system load is low, but

Table 4.3: Employees - Result Overview for Different Charging Strategies

Parameter Description	AFAP	EEX	LF	Residual	WL
Rel. Wind-Power Share	7.42%	11.02%	9.92%	11.89%	14.72%
Rel. Wind Increase to AFAP	-	48.51%	33.69%	60.24%	98.38%
Average Load Factor	77.89%	57.13%	53.41%	54.09%	62.01%
Cost Comparison					
Avg. Costs [Eur/ week]	8.42	2.32	3.04	3.03	4.31
Cost Diff. to EEX [Eur/ week]	6.10	-	0.72	0.71	2.08
Avg. kWh Costs [Eur/kWh]	0.244	0.067	0.088	0.088	0.125
Rel. Savings to AFAP	-	- 72.44%	-63.89%	64.01%	48.81%

wind power generation substantial. This helps to balance the variable generation pattern and, depending on the deployment scenario, can help to stabilize the power system. *Residual* has a wind utilization share of 11.89% on average over the year, which is substantially higher than the *LF* strategy. Nevertheless it has the overall second lowest average load factor with 54.09%, with less than one percent more than the in these terms optimal *LF* strategy. In addition, it can be observed that the *Residual* load strategy utilizes even more wind-power than the *EEX* strategy. It thus combines the advantages of off-peak charging while maintaining a responsiveness to high wind power generation situations.

When the costs incurred by the different charging strategies (RQ 1.2) are compared, it is interesting to observe that *LF* comes at 0.72 Eur., *Residual* at 0.71 and *WL* at 1.98 Eur. higher cost per week as compared to charging in the *EEX* strategy. The costs in this case are 2.32 Eur. per week, which yields a weighted average price of 0.067 Eur/kWh and represents the individual average minimum payment per week in this sociodemographic group. *AFAP* in contrast does not consider the variable price for its charging decisions and thus incurs the highest average costs per week with 8.42 Eur. and a kWh price of 0.244 Eur/kWh. This considerable difference can be explained by the charging times of *AFAP*, which are predominantly in the late afternoon and evening hours, typically a time of higher demand and thus prices (cf. Figure 4.13).

The *LF* strategy has a focus on global system stability, but does perform quite well in economic terms, as times of low overall system load have lower prices. The weekly average costs of *LF* are with 3.04 Eur. 63.89% lower than the payments in the *AFAP* case. *Residual* has a similar cost level as *LF* but performs better with regard to the wind-power share that is used on average for charging.

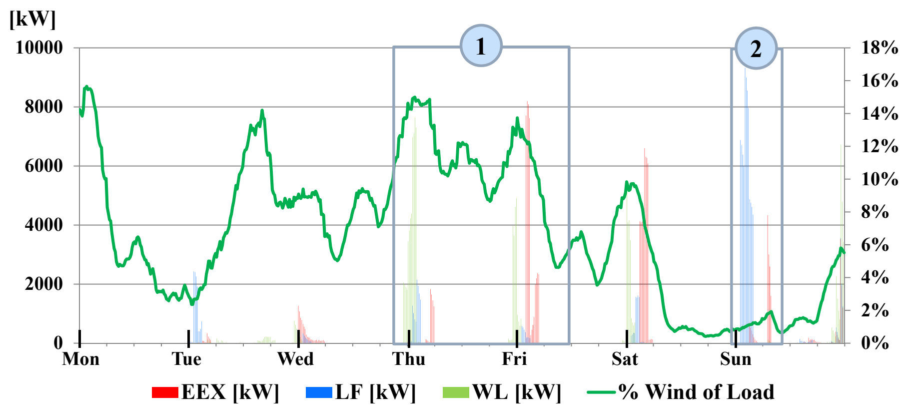


Figure 4.5: Employees: Charging demand for the SC strategies in relation to relative wind power share (week 37).

Figure 4.5 exemplarily shows the results of one week. This week exhibits rather volatile wind power in-feed and representative curves for both, average load factor and EEX-prices. It can be observed that in the middle of the week (area 1), on the night from Wednesday to Thursday, a high wind power in-feed is used for charging for most of the 893 EVs with a total load of around 8,000 kW. Other *WL*-charging occurs in the subsequent nights through Saturday morning. Except from Sunday evening *WL*-charging does not occur anymore. In contrast to this *LF*-charging can predominantly be observed in the night from Saturday to Sunday, and thus, does not exhibit a high share of renewable energy (area 2). *EEX*-charging is using a higher share of wind power as it often starts with a small delay after the wind power peak has occurred (c.f. right side of area 1 and after the subsequent wind power peak).

Figure 4.6 shows *EEX* and *LF* charging in comparison to their determining parameter in the same week as above: the scaled EEX-price and the system load factor, both depicted on the secondary axis. The resulting load is assigned to the primary axis. In this illustration, the resulting load patterns of the EVs can clearly be attributed to the relative local minima of the objective value, being the lowest prices in the EEX-case and the lowest system load factor in the *LF* case. It can also be observed that even though they are often occurring during similar time intervals *LF* and *EEX* charging do not always exactly coincide. This is an explanation for the differing overall individual cost level described above.

The *Residual* load strategy and its load pattern for the exemplary week are depicted in Figure 4.7 in comparison to the wind-power generation and the *LF* strategy. Even though the similarity between these two strategies can clearly be

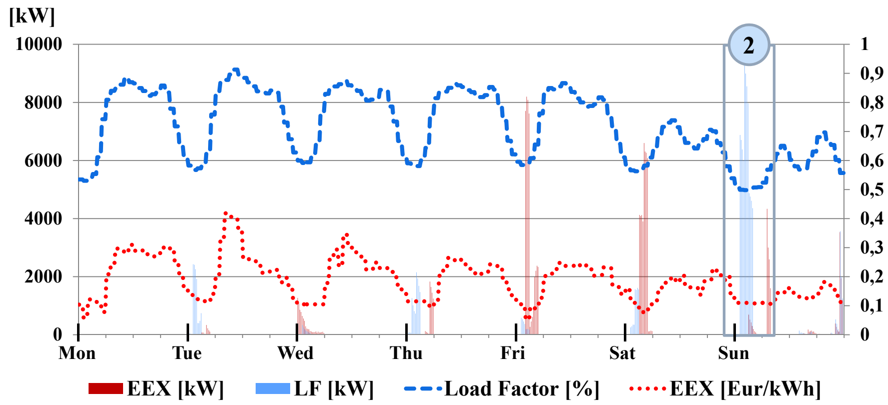


Figure 4.6: Employees: Charging demand for the EEX and LF strategy in relation to EEX-prices and load factor (week 37).

seen, in particular during the Sunday morning charging peak, the figure also shows the difference between the strategies. Especially the charging peak of *Residual* charging on Thursday morning shows the responsiveness to a higher wind-power share in the system during situations of low load.

Figure 4.8 depicts the same week, but adds the perspective of the total system load and the relative wind-power generation share to the picture. Also the charging load of the *EEX* and *WL* strategy are compared to the load of the *Residual* strategy (charging load is consistently depicted with respect to the primary axis). It can be observed that *WL* and *Residual* both have one of their main charging peaks during the mentioned time slots on early Thursday morning in this week. *WL* also has additional peaks in the following nights whereas *Residual* concentrates demand during the load minimum of the week on early Sunday morning. *EEX* in turn can be observed to always charge during the early morning hours slightly after the minimum system load.

This example shows how each of the strategies *EEX*, *WL* and *Residual* considers the impact of wind-power for the coordination of its charging actions. *EEX* charges during times of low prices during the night, but is also sensible to high wind-power generation in particular during times of low load. *Residual* considers the system load factor and thus reacts even stronger to high-wind, low-load situations. *WL* in turn maximizes the relative wind share at which charging occurs but is also more likely to charge during medium or low load situations. This can be observed e.g. for Tuesday afternoon, where only little charging occurs even though the relative wind-power share maximum exists there. The strategies thus all take full advantage of the demand flexibility of the EVs in or-

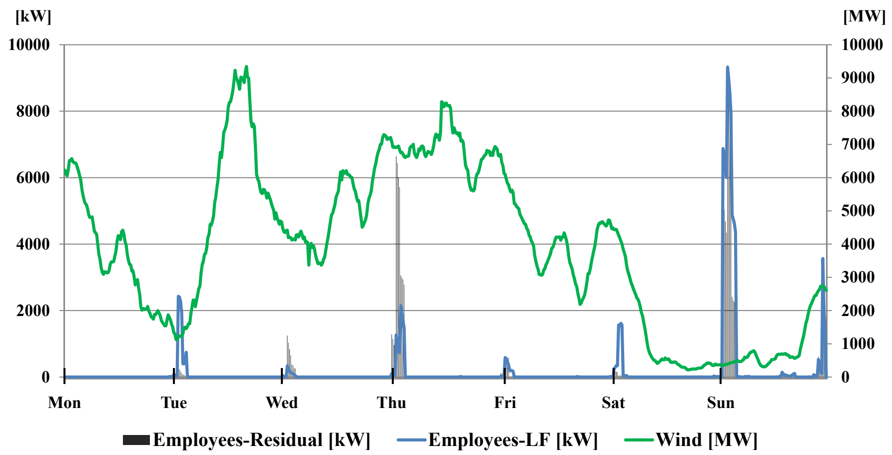


Figure 4.7: Employees: Charging demand for the SC strategies (*Residual*, *LF*) in relation to relative wind power share (week 37).

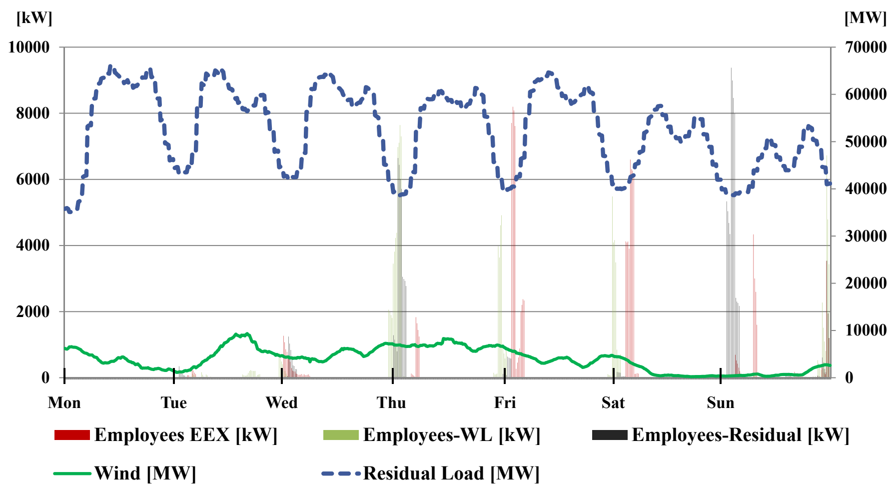


Figure 4.8: Employees - Charging demand for the SC strategies (*EEX, WL, Residual*) in relation to relative wind power share and system load (week 37).

der to fulfill their particular objective. As mentioned above one must be aware that the strategies profit from the assumption of securely available information, which leads to a substantial demand concentration. This concentration can be problematic for the line and transformer capacity limits if EVs are concentrated at one particular location.

In an overall comparison of the five strategies it is obvious that *AFAP* is a simple to implement, but with respect to economic and renewable energy utilization objectives, unattractive strategy with a low performance. *EEX* charging in turn maps quite well on different objective criteria like wind-share and system load. This appears reasonable since in times of high demand prices are high and in times of high wind in-feed the prices are low, especially if demand is also low during the particular time. The price-reducing effect of wind power on the EEX-price was empirically shown and is commonly referred to as the merit order effect (cf. (Sensfuss et al., 2008; Nicolosi, 2010)). *Residual* and *LF* charging in turn emphasize the aspect of system peak avoidance but do not perform as well in economic terms as *EEX* does. *Residual* appears to be a good compromise in the direction of a higher wind-power share which is utilized for charging while maintaining a reasonable cost level and at the same time avoiding overall system peak and thus contingency situations.

4.2.6 Results Retired

For the *retired* EV customers the results are to some extent similar to the *employees*. The wind power utilization share is higher for all investigated strategies but exhibits the same general performance order with *AFAP* having the smallest average wind-share. The utilized share of wind-power for *AFAP* is slightly higher than in the employee case, but still below the average value of wind power of 7.98% for 2007. In the *WL*-charging strategy the wind-share is 15.57% and therefore higher as compared to the same value for *employees*. This can be seen as a first indication of the substantially higher flexibility of *retired* EV-owners in comparison to *employees*, (cf. Table 4.4). In conclusion the charging strategies can be ranked with respect to their wind-share as follows: *WL*, *Residual*, *EEX*, *LF*, and finally *AFAP*[1].

The system compliance of the *LF* is very high as the average load factor for this strategy is only 52.09%, which is about 10% over the absolute minimum load factor occurred in 2007 of 42.86%. At the same time *retirees* are able to charge in

[1]WL is the benchmark in this case, since the optimization criteria is to charge in periods of a high wind-share.

Table 4.4: Retired - Result Overview for Different Charging Strategies

Parameter Description	AFAP	EEX	LF	Residual	WL
Rel. Wind-Power Share	7.51%	11.45%	10.50%	12.13%	15.57%
Rel. Wind Increase to AFAP	-	52.46%	39.81%	61.51%	107.32%
Average Load Factor	77.71%	56.22%	52.09%	52.78%	61.66%
Cost Comparison					
Avg. Costs [Eur/ week]	4.44	1.14	1.48	1.52	2.25
Cost Diff. to EEX [Eur/ week]	+3.30	-	+0.34	+0.38	+1.11
Avg. kWh Costs [Eur/kWh]	0.243	0.062	0.081	0.083	0.123
Rel. Savings to AFAP	-	74.32%	66.66%	65.76%	49.32%

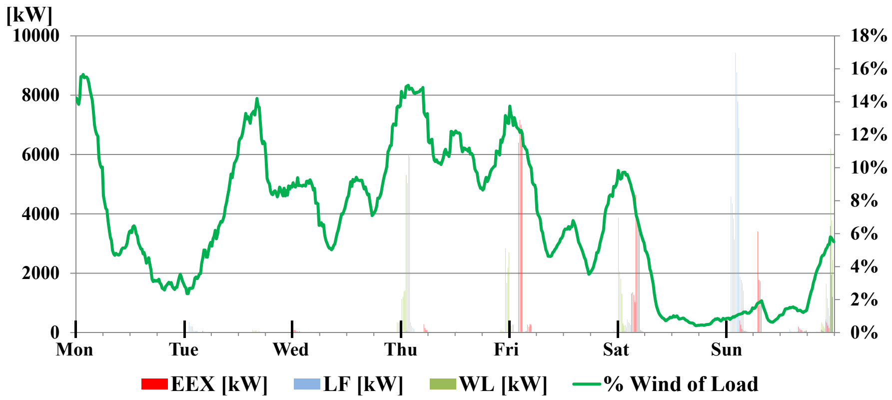


Figure 4.9: Retired - Charging demand for the SC strategies in relation to relative wind power share (week 37).

periods of a lower average load factor as compared to *employees*. With respect to their system load impact the charging strategies can be ranked as follows: *LF, Residual, EEX, WL*, and *AFAP*[2]. The *Residual* charging strategy again performs well with respect to its average system impact and the average share of wind-power employed for charging which increases the utilized wind share by 21.7% as compared to *LF* while incurring only slightly higher costs of 2.7% in this case.

The absolute costs for all strategies are considerably lower for *retirees* as compared to *employees* which can be clearly assigned to the fact that the overall driving distance is with an average of 119 km only about half as high as for *employees*. *EEX* is the cost benchmark at 1.14 Eur. per week. *AFAP* charging exhibits

[2]LF is the benchmark in this case, since the optimization criteria is to charge in periods of low load.

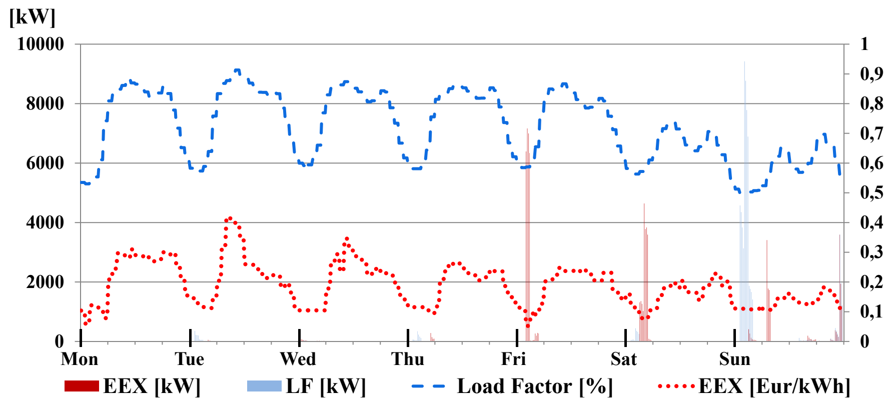


Figure 4.10: Retired - Charging demand for the EEX and LF strategy in relation to EEX-prices and load factor (week 37).

the worst cost performance at with 4.44 Eur. per week. *LF* and *Residual* incur higher costs than *EEX* with 1.48 and 1.52 Eur. per week on average. These values are still substantially below the level of 2.25 Eur. per week that is accounted for in the *WL* strategy. The cost differences are also reflected in the kWh price for the different strategies. They range from 0.062 Eur. per kWh (*EEX*) to 0.243 Eur. per kWh (*AFAP*). Besides the absolute cost level, the relative differences between *employees* and *retriees* on a relative level remain quite low. There is a clear tendency for lower kWh prices for *retirees* but in the aggregate evaluation undertaken in this section, the overall cost levels are still similar. An analysis further investigating the load flexibility potential of *retirees* will follow in Chapter 5.

For comparison to the *employees* Figure 4.9 shows the relative wind power share and the resulting load for *retired* EV-owners resulting from the coordinated charging strategies. Similar to the *employee* results *WL* charging occurs mostly in the night from Wednesday to Thursday, and the two following nights, as these mark the periods with a wind power share of 10% or more. The peak load caused by *WL* is only about 6000 kW for a total of 937 EV-owners which also indicates that only about 60% of them are charging during this time slot. The following demand in *WL* is not surpassing 4000 kW which shows that due to the shorter distances and lower resulting demand, *retired* EV customers have a high degree of flexibility in their charging time decisions. This flexibility leads to the interesting, and potential problematic situation that nearly all of the *retired* EV customers are charging in the night from Saturday to Sunday in the *LF* charging scheme, thus creating a peak demand of over 9000 kW. This simultaneity problem is not only confined to this strategy and will be discussed in the following section, as

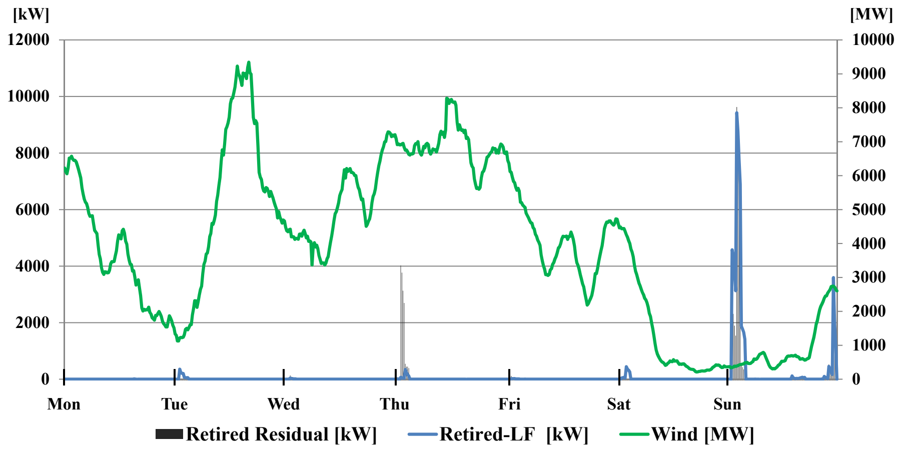


Figure 4.11: Retired: Charging demand for the SC strategies in relation to relative wind power share (week 37).

it is partly a consequence of the assumptions of the model applied.

Figure 4.10 shows the resulting demand in the *EEX* and *LF* schemes in relation to the load factor and the EEX-price of week 37. It can be observed that most of the *EEX* demand occurs on Friday and Saturday morning. The *EEX* demand is similarly delayed as in the case for the *employees*, a fact that can be accounted to the lower price induced by lower demand in the night hours, coupled with a higher in-feed of wind power.

Figure 4.11 shows the same week for the *Residual* charging strategy as above. It can be observed that the resulting general load behavior is similar to the one of the *employees*. The distinction between *LF* and *Residual* is more accentuated for *retirees*. The particular difference is the charging peak occurring on early Thursday morning with a maximum around 4000 kW in the *Residual* charging strategy, whereas *LF* does not charge a significant amount during these time slots. As mentioned above *LF* concentrates most of its charging activity on early Sunday morning, the time of the system minimal load in this week.

When the resulting load of *Residual* is depicted in the context of the total system load and the corresponding wind-power share in Figure 4.12, one can see that the charging times, in particular on Thursday have a high overlap with the *WL* strategy. *EEX* also has a similar charging pattern as in the *employee* case, but can also concentrate its charging actions during Friday and Saturday morning. This shows that on average *retirees* have the flexibility to charge only once per week and can thus choose the optimal time slots with respect to their respective optimization objective. This increases their adoption potential under the

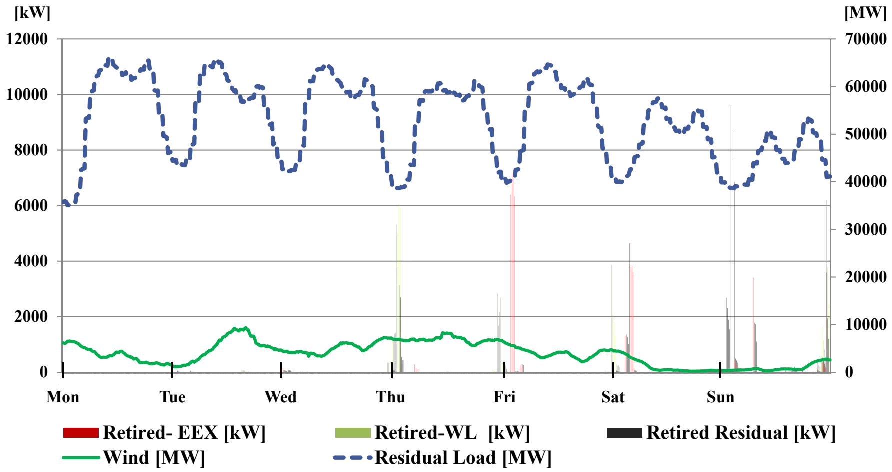


Figure 4.12: Retired: Charging demand for the SC strategies in relation to relative wind power share (week 37).

assumed conditions, but can in a more constrained setting with respect to the quality of available information also lead to the problem of fully charged batteries despite a higher availability of renewable power in later time intervals. The following section will thus discuss the presented findings and challenges that can result from them.

4.2.7 Conclusion

The results of the simulation for the smart charging strategies show that in comparison to uncoordinated *AFAP* charging the utilization of wind power can be nearly doubled by the *WL* strategy and significant cost reductions of more than 70% are possible in the *EEX* strategy for both analyzed driver groups. All coordinated charging strategies have a lower load factor than *AFAP*. These results demonstrate the relevance of charging coordination for EVs. The *Residual* charging strategy offers an interesting combination of different optimization objectives. It enables substantial savings of at least 64.01% as compared to *AFAP*, while seeking to charge at times of low overall system load and still utilizes a higher wind-power share than most of the other charging strategies.

The coordination approach based on ex ante known information can lead to unwanted effects as EV customers jointly start shifting their charging times according to the given objective criteria. This behavior in turn can lead to new peaks in the power system especially when high power connection ratings (in this approach 10.5 kW) are assumed and EVs are not spatially dispersed. High

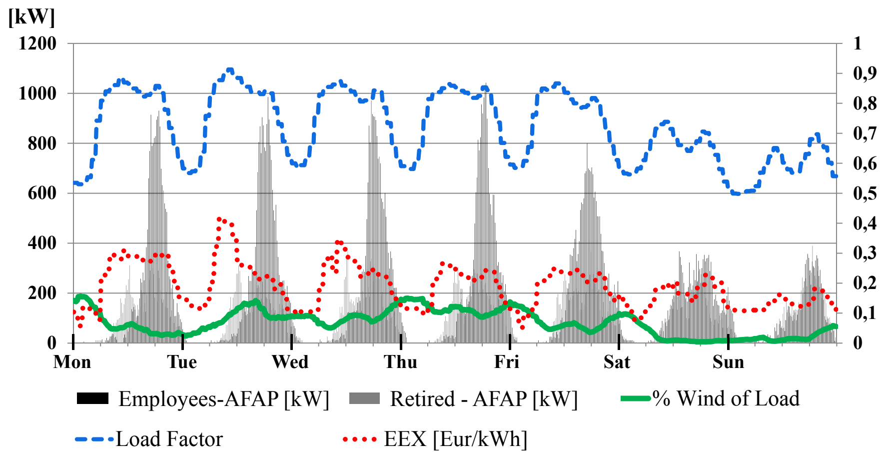


Figure 4.13: Overview of uncoordinated AFAP charging demand and charging signals for one week (week 37)

peaks can be observed in Figure 4.5 to 4.12. In contrast to the *SC* strategies demand is more distributed in the *AFAP* case since every EV-owner charges when she arrives at home. Even though this demand is less concentrated it has a number of other drawbacks, like the high costs due to peak time charging and the overall negative system impact due to a high load factor. In addition it was also demonstrated above that *AFAP* is not suited to use a higher renewable energy share in the case of wind-power. Figure 4.13 depicts the *AFAP* demand of *employees and retirees* in relation to the load factor, the EEX-price and the relative wind power share. As *AFAP* demand is similar in every week one can observe that with respect to the adoption of renewable, and in particular volatile sources, *AFAP* will only fit by coincidence.

In order to address the high load concentrations in the coordinated charging approaches, dynamic charging signals which are adapted according to the local distribution network situation in addition to the availability of RES and low energy prices could be introduced. Another approach to ameliorate the accentuated peaks could be to lower the available charging powers. The effect of this constrained grid connection is further analyzed in Section 5.3, where a supply based perspective under consideration of physical generation constraints is further investigated. For a real world deployment one needs to consider that not all EV customers will have the same expectations about prices and the system state, so that peaks are not likely to be that accentuated as observed in this analysis which can be seen as a benchmark for what can be achieved in the presented scenarios.

Table 4.5: Overview of linear storage costs for Li-Ion batteries with an assumed life time of 2200 full cycles.

Battery Costs	**Avg. Costs [Eur] p.y.**	**Avg. Cost [Eur] p.w.**
Employees		
0.1 [Eur/kWh] p.c.	179.21	3.44
0.2 [Eur/kWh] p.c.	358.43	6.89
0.4 [Eur/kWh] p.c.	716.86	13.78
Retired		
0.1 [Eur/kWh] p.c.	95.07	1.83
0.2 [Eur/kWh] p.c.	190.15	3.65
0.4 [Eur/kWh] p.c.	380.30	7.31

The storage costs have not been accounted so far, as they are the same for the analyzed strategies. Table 4.5 shows the battery storage costs incurred for the average usage for the two groups under consideration of different usage costs ranging from 0.1, 0.2 and 0.4 Eur/kWh per cycle (p.c.). The calculation assumes 2200 cycles for the lifetime of Li-Ion based batteries, which are predominantly used for EVs. This in turn leads to specific battery replacement costs of 220, 440 and 880 Eur/kWh (Kempton, 2000) (disregarding non-linearities and possible additional capital costs). The calculation considers the actual battery usage of both groups. The storage costs are not attributable to the specific charging strategy in this case, but more to external factors like operation environment temperature and depth of discharge (DoD) depending on general usage patterns.

More recent work from (Bashash et al., 2011) and (Peterson et al., 2010) suggests that DoD is only a proxy for the absolute energy throughput for a storage device which in turn is identified as one of the main driving forces behind battery degradation. Nevertheless the different (linear) storage cost levels show that if battery costs are not higher than 0.2 Eur/kWh, operational savings as reported above represent a substantial benefit in particular for the employees.

Since high storage costs are still one of the main impediments of mass EV adoption, the next section will explicitly consider them in the individual objective function of every EV and thus will improve the economic assessment and evaluation of the particular value of battery friendly charging coordination strategies.

4.3 Individual Economics: Vehicle-to-Grid Model

Following the analyses in Section 4.2 with a focus on the ability of individual EVs to coordinate their charging demand with respect to different optimization objectives, this section extends the interaction of the EVs with the power system, by assessing their short term storage capabilities in an economic manner.

Considering EVs as an active part of the power system was first done by (Heydt, 1983) and further analyzed in (Kempton and Letendre, 1997; Kempton and Tomić, 2005a). The latter studies introduced the term Vehicle-to-Grid (V2G), which captures the EV's ability to feed back electricity into the power grid at times when this is required for grid support or economically beneficial to perform arbitrage. It is shown that vehicles can achieve additional profits when participating in primary and secondary regulation services in the Californian energy market, as they are idle 96% of the time (Kempton and Tomić, 2005a). Besides the possibility to directly participate in regulation markets, one of the first steps for the integration of EVs into the power system is to coordinate charging in such a way that it is beneficial for the EV-owner and the power grid. This coordination can be achieved if EVs can employ smart grid technologies to communicate their demand flexibility and participate in energy markets. In contrast to existing studies (cf. Section 2.6), this section thus adds an individual and predominantly economic perspective to the research area of EV charging coordination.

Most models in literature consider driving behavior of EVs only based on general assumptions about mobility habits. These either build on average statistical data or on simplified assumptions of availability and plug-in rates. The following analysis builds on the empirical data basis of the German Mobility Panel, a mobility survey reflecting different sociodemographic groups (i.e. employees, retired persons) to model mobility patterns as a basis for the analysis.

Given real-life driving profiles and a variable pricing scheme based on German hourly wholesale electricity prices of 2007, the following research questions are investigated:

RQ 2 - Economic Evaluation under Consideration of Storage Costs: *What are the individual costs, including battery degradation, of charging electric vehicles employing a cost minimizing charging strategy while still fulfilling the given mobility profile, for the sociodemographic groups of employees & retired?*

RQ 2.1 - Economics of V2G under Consideration of Storage Costs: *Which additional profits can be generated for the two groups if electricity can be sold back to the grid in a V2G operation strategy, while driving needs are still fulfilled and battery degradation is accounted for?*

The following analysis substantially builds on and extends (Schuller et al., 2013). The analysis is structured as follows: Section 2 gives a brief overview of context of the analysis, Section 4.3.2 specifies the simulation input data and its sources. Section 4.3.3 and 4.3.4 define the simulation model with its parameters, simulation assumptions, and the objective functions of different charging strategies. Sections 4.3.5 - 4.3.7 present and discuss the simulation results and Section 4.3.8 concludes on the obtained results.

4.3.1 Vehicle-to-Grid: Related Work

Electric vehicles are part of two major systems – the individual transportation sector and the power system (Blumsack and Fernandez, 2012). Consequently, an active field of research with interdisciplinary questions from transportation, electrical and mechanical engineering, chemical and material science and especially power system economics has developed. The impact of EVs on power systems and emissions has been investigated in several scenarios (Kintner-Meyer et al., 2007), (Sioshansi and Miller, 2011). This work shows that local emissions can be reduced significantly, and also global emissions can be reduced if charging demand is coordinated by the ISO (Independent System Operator) such that cleaner generators such as natural gas are used to cover EV demand.

The flexibility in charging demand exhibited by EVs can be employed with different objectives. The most relevant are distribution grid loss minimization, cost minimization given a variable pricing regime, or direct market participation and system support through provision of regulation services and balancing of renewable generation (Richardson, 2013). For the case of distribution loss prevention, it was shown by Peças Lopes et al. (2009) and Acha et al. (2011) that charging coordination will increase the utilization of grid resources and support a higher diffusion rate of EVs without the necessity of grid reinforcements. In the particular residential distribution area case, the share of EVs integrated could be increased from 10% to 52% of the households through charging coordination. Further analyses from Gonzalez Vaya and Andersson (2012) include the transmission levels and assess different centralized and decentralized control approaches. Findings suggest that peak loads can be avoided, grid assets are not overloaded, and generation costs can be reduced. Work of Flath et al. (2013) and Gerding et al. (2011) shows that decentralized charging decisions based on little information can also be successful to achieve efficient economic outcomes while considering system constraints.

Concepts for aggregator architectures are presented in (Sandels et al., 2010; Guille and Gross, 2009) and further analyzed in a regulation and V2G context by (Andersson et al., 2010; Sortomme and El-Sharkawi, 2011; Bessa et al., 2012) and (Ortega-Vazquez et al., 2012). Following the first general assessment of Kempton and Tomić (2005a), Andersson et al. (2010) show that for about 3-5% of the respective vehicle fleets a participation in the German and Swedish regulation markets would be profitable. Further work focusing on the wholesale market participation and energy arbitrage by Peterson et al. (2010) shows that V2G can be profitable, but does not yield very high revenues for EV owners and is not competitive for storage periods longer than a day.

This analysis extends the literature by considering the individual economic perspective of the EV owner. The general applicability of EVs based on a large set of empirical data is assessed and the economic potential of different charging strategies including a V2G operation scheme is evaluated.

4.3.2 Input Data

The three key empirical data sources for the simulation are electricity market prices, driving behavior of the EV owners, and the EV specifications.

Price Data

The data for market prices used for the simulation corresponds to the hourly intraday wholesale power price time series in 2007 from the European Energy Exchange (EEX, 2007). In order to obtain a more illustrative economic analysis at the end consumer level the price was adapted according to the average retail rate of 20.12 ct/kWh for this year (BNetzA, 2008). The general data basis is thus similar to Section 4.2, but as it will be described in more detail in the following paragraph, the scaling approach was adapted in order to allow for a more accurate representation of current regulation requirements.

The variable end consumer price has three main components that must be considered: wholesale energy costs (reflected by the EEX-intraday prices with an average value of 6.88 ct/kWh), grid and additional fixed fees (10.02 ct/kWh)

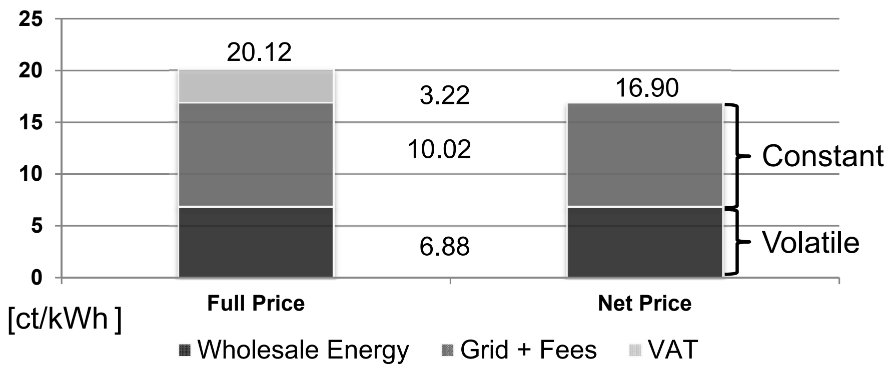


Figure 4.14: Average end consumer price components and average net price employed for the economic analysis.

and value added tax (VAT) of 19%, cf. Figure 4.14. The average retail rate includes the VAT, but as the possibility of energy arbitrage is investigated tax is not supposed to have an impact on the arbitrage decision, since the tax amount paid for consumption must be revenue neutral when the energy is sold back to the power grid. Following this, the price level considered consists of the EEX-price and the fixed fees, which cover the grid integration costs for the respective customer. The average power price level of the time series is thus adapted to 16.90 ct/kWh, the average costs without sales tax. Since the payment for grid and fees is fixed, both for selling and purchase of power, the decision whether energy arbitrage and i.e. a V2G operation mode is chosen only depends on the wholesale energy price and its spread. In particular, the grid and fees amount is assumed to be reimbursed when electricity is sold back to the grid. This concept is already partly in place in the so called avoided grid usage fee[3] for generators.

The described price level thus reflects the average hourly dynamic end-consumer prices of this year, without dynamic tax effects but including all fees.[4]

Mobility Data

The driving behavior builds on the same data set from the German Mobility Panel (MOP) which is also employed above (BMVBS, 2008). The initial data set provides 17,705 trip profiles (by all means of travel), after data cleansing and filtering around 11,400 driving profiles could be used for the analysis (cf. Chapter

[3]cf. Paragraph 24 of the German Energy Act: http://www.gesetze-im-internet.de/enwg_2005/__24.html

[4]Fees encompass: distribution, transmission, renewable energy and CHP subsidy, federal and regional charges.

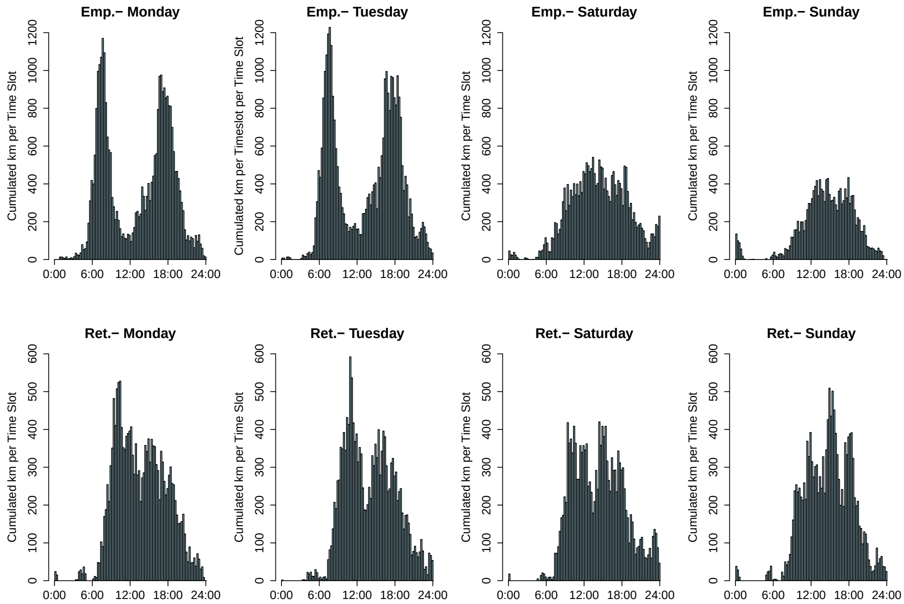


Figure 4.15: Weekday and weekend cumulated driving distances of employees and retired persons in the MOP.

3). A driving profile includes all car trips within a specified week of the year made by a certain person. Assuming that vehicle owners will drive their EVs in a similar way as they today drive their internal combustion engine vehicles (ICEVs), this data is used for the simulation of EVs. The driving profiles have been split according to two different sociodemographic groups of people: employees and retired people. For the analysis, the 1,000 most up-to-date profiles of each group are employed. Figure 4.15 provides and exemplary overview of the driving patterns of *employees* and *retired* persons, the groups with the most contrasting driving behavior.

EV Specifications

The BMW Mini E again serves as the reference vehicle, which also enables a general comparison with the results from other sections. Table 4.6 provides an overview of the technical specifications like battery capacity, specific consumption and charging rates. In addition to the technical vehicle specifications, parameters that determine the V2G interaction ability are also specified. In this context battery degradation must also be considered. Following Peterson et al. (2010) and Bashash et al. (2011) the main determinants of battery degradation

Table 4.6: EV Specifications

Parameters[a]	**BMW Mini E**
Power Consumption [kWh/km] [b]	0.14
Max Range [km]	250
Top Speed [km/h]	152
Full Charging Time [h] [c]	3
Full V2G Discharging Time [h] [c]	3
Charging Specifications [V, A]	240, 48 (US) 230, 16/32 (DE)
Capacity [kWh]	35
Usable Capacity [kWh] [d]	31.5
Battery Type	Li-ion
Charging Efficiency [%] [e]	93
Discharging Efficiency [%] [e]	93

[a] If not stated differently, parameter specifications are found in (BMW, 2009).

[b] Power consumption $= \frac{\text{capacity}}{\text{max range}}$, average consumption value, independent of individual factors (e.g. driving style, speed, terrain).

[c] Assumption: full charging time = full discharging time.

[d] Assumption: depth of discharge (DOD) = 90%

[e] Assumptions about parameters based upon information provided in (Tomic and Kempton, 2007).

are the general energy throughput over the lifetime of the battery and the charging power or current expressed by the C-rate. A more detailed description of the technical implications in the model is given in Section 4.3.4.

4.3.3 Model Definition

The following subsections describe the assumptions that are made, in addition to the ones from Section 4.2 with respect to the optimization model and the simulation implementation. The different charging strategies which only encompass AFAP, EEX and a V2G strategy are formalized with their corresponding objective functions and the necessary constraints that incorporate the technical restrictions and scenario parameters.

Assumptions and Parameters

The following assumptions are made within the model setting. Unless stated other the assumptions from Section 4.2.2 also apply here:

- The volatile component of end consumer electricity prices change proportionally to wholesale electricity prices.

- EV-owners can buy electricity at end consumer prices, sell at wholesale prices and receive a grid feed reimbursement in this case.
- Driving patterns and electricity prices are ex-ante known for the optimization horizon.
- Mobility has to be guaranteed, i.e., the battery is always charged such that the next trips are possible.
- The additional load caused by the small number of charging EVs in our study has no influence on electricity prices. EVs are price takers.
- EVs can only be connected to the power grid at the homes of the owners. Therefore, charging and discharging (i.e. selling electricity) is only possible when the EV is parked at home.
- When parked at home, EVs can always charge and discharge the battery at any time within the technical constraints of the battery (including state of charge (SOC)).
- The time frame of the analysis is one week with 15 min. time slots resolution (T=672).
- The battery of the EV is charged to 75% at the beginning of the week and has to reach the same level at the end of the week.

The assumptions are designed to represent the present and the near future and are kept reasonably conservative with respect to the availability of charging and discharging opportunities. Table 4.7 provides an overview of the model parameters used in the subsequent analyses.

Charging Strategies

The simulation implements three different charging strategies: *as fast as possible charging, AFAP*, *Smart Charging*, and *Vehicle-to-Grid* (V2G). In AFAP mode, the EV immediately starts charging when connected to the grid and stops charging when either the battery is fully charged or when the EV gets disconnected from the power grid (Equation 5.17). Smart Charging identifies the cost-optimal charging times for the vehicle owner in order to complete her driving profile and thus corresponds to the EEX charging strategy from Section 4.2. Vehicle-to-Grid goes one step further than Smart Charging enabling the EV owner to sell electricity while still charging in a cost-minimal way. In both controlled charging approaches, the charging and discharging time-steps and the amount of energy charged and discharged during these time-steps are the decision variables of the optimization problem. The formal description of the different strategies slightly differs in this section in order to account for battery degradation costs and to

Table 4.7: Model Parameters

Storage System and Infrastructure Parameters		
Battery capacity	$\overline{SOC}$	(kWh)
Charging efficiency	η_c	(%)
Discharging efficiency	η_d	(%)
Energy storage cost	ψ_{en}	(Eur/kWh)
Charge rate storage cost	β_{cr}	(Eur/kWh)
Maximum charge amount per time slot	$\overline{\varphi}$	(kWh)
Initial EV battery SOC	SOC_{init}	(kWh)
Terminal EV battery SOC	SOC_{end}	(kWh)
Infrastructure Cost	K_f	(Eur/week)
Market and Consumer Parameters		
Price per energy unit at time t	p_t	(Eur/kWh)
Energy consumption at time t	d_t	(kWh)
Location of the EV at time t	z_t	(binary)
Decision Variables		
Charge parameter for at time t	φ_t	(kWh)
Net charging amount	ϕ	(kWh)
V2G parameter for at time t	λ_t	(kWh)
SOC level for at time t	SOC_t	(kWh)

enable a more comprehensive model representation.

AFAP Charging

$$\varphi_t = \begin{cases} \min\{\overline{\varphi}_t, \overline{SOC} - SOC_t\} & : \text{if } SOC_t \leq \overline{SOC} \\ & \quad \text{and } z_t = 1 \\ 0 & : \text{if } z_t = 0 \end{cases} \tag{4.16}$$

$$z_t = \begin{cases} 1 & : \text{EV at home within time step } t \\ 0 & : \text{otherwise} \end{cases} \tag{4.17}$$

The payment resulting from this strategy is the sum of energy charged in the time slots that are predominantly determined by the arrival times at home, and do not incorporate any economic decision-making rationale. The payment is given in Equation 4.18 and consists of energy costs and battery degradation costs.

$$P = \sum_{t=1}^{T} \underbrace{p_t \cdot \varphi_t}_{\substack{Energy \\ Costs}} + \underbrace{\varphi_t^2 \cdot \beta_{cr}}_{\substack{Power-related \\ Battery \\ Degradation}} + \underbrace{\varphi_t \cdot \psi_{en}}_{\substack{Energy-related \\ Battery \\ Degradation}} \tag{4.18}$$

Smart Charging

Smart Charging minimizes costs by choosing appropriate charging time slots. In contrast to AFAP charging, it endogenously considers the degradation costs resulting from higher charging powers, while the degradation resulting form energy throughput remains the same as in the AFAP charging case. The payment K_f is a constant added to account for the Smart Charging infrastructure costs.

$$\min_{\varphi} \sum_{t=1}^{T} p_t \cdot \varphi_t + \varphi_t^2 \cdot \beta_{cr} + \varphi_t \cdot \psi_{en} + K_f \tag{4.19}$$

subject to, ($\forall t \in T$):

$$SOC_t \geq 0 \tag{4.20}$$

$$SOC_t \leq \overline{SOC} \tag{4.21}$$

$$\varphi_t \leq z_t \cdot \overline{\varphi_t} \tag{4.22}$$

$$SOC_t = SOC_{t-1} - d_t + \eta_c \cdot \varphi_t \tag{4.23}$$

$$SOC_1 = SOC_{init} - d_t + \eta_c \cdot \varphi_1 \tag{4.24}$$

$$SOC_T = SOC_{end} \tag{4.25}$$

$$p_t, d_t, \eta_c, \eta_d, \varphi_t, \lambda_t, \psi_e n, \beta_{cr} \geq 0 \tag{4.26}$$

Equations 4.20 – 4.22 represent the properties of the SOC and the maximum power rating which is used for charging. $\overline{\varphi_t}$ incorporates the maximum energy amount that can be charged during one 15 minute time slot. Equations 4.23 – 4.25 account for continuous battery state transitions, initial and terminal SOC values.

Vehicle-to-Grid

The objective function for the V2G case extends the Smart Charging objective by accounting for revenues that can be achieved from energy sales.

$$\min_{\varphi,\lambda} \sum_{t=1}^{T} p_t \cdot (\varphi_t - \eta_d \cdot \lambda_t) + \varphi_t^2 \cdot \beta_{cr} + \varphi_t \cdot \psi_{en} + K_f \tag{4.27}$$

Most constraints are similar to the *Smart Charging* case, with exception of the following, incorporating the discharging capability and the net energy flow from or to the battery:

$$SOC_t = SOC_{t-1} - d_t + \eta_c \cdot \varphi_t - \lambda_t, \quad \forall t \in T \tag{4.28}$$

$$SOC_1 = SOC_{init} - d_t + \eta_c \cdot \varphi_1 - \lambda_1 \tag{4.29}$$

$$\phi_t = \varphi_t - \lambda_t, \quad \forall t \in T \tag{4.30}$$

$$SOC_T \geq SOC_{end} \tag{4.31}$$

The investment costs for the EVs are not included in the analysis, since the focus is on the comparison of the different charging strategies. Basic charging infrastructure costs are not considered, as charging equipment is needed regardless of the charging strategy employed.

4.3.4 Scenario Setup

The simulation scenarios have been defined along the three main parameters *charging strategy*, *driving profile group* and *battery degradation cost*. The values for each parameter are as follows:

- *Charging strategy:* AFAP Charging, Smart Charging, Vehicle-to-Grid
- *Driving profile group:* employees, retired people
- *Energy-related battery degradation cost:* 0.05 Eur/kWh, 0.1 Eur/kWh, 0.2 Eur/kWh
- *Power-related battery degradation cots:* 0.01 Eur/kWh, 0.02 Eur/kWh.

Upgrades incorporating communication infrastructure, additional metering and power electronics for the implementation of Smart Charging and V2G are considered following the numbers provided by (Tomic and Kempton, 2007): For AFAP charging no additional infrastructure costs are incurred, for Smart Charging the additional costs are 0.35 Eur/week and 1.27 Eur/week in the V2G case. The different costs levels are due to additional communication infrastructure, metering and power electronics required *on top* of the standard charging infrastructure.

The main parameters are closely interlinked when determining the saving potential for each scenario. The charging strategies influence the timing of charging periods and allow for load shifting to low price periods, but the overall benefit potential is constrained by the time of presence at home and the capacity and charging power of the EV. In order to address the uncertainty concerning battery degradation costs two main factors to account for battery wear are employed. First the overall energy throughput of the battery is a main factor of capacity loss, as the number of lithium ions that can be intercalated is reduced through irreversible chemical processes over time as described by (Peterson et al., 2010). Second the charging power employed for charging is taken into account. Following the work presented by (Bashash et al., 2011), additional costs that are incurred when the battery is charged at higher C-rates are assumed. A quadratic term is incorporated in the objective function to reflect this degradation behavior. This modification provides incentives for Smart Charging to avoid high charging power levels.

Building on cost estimates of the California Air Resources Board's (CARB) Battery Technical Advisory Panel which considers scaling cost effects, vehicle li-ion batteries could cost as little as 150 USD/kWh (108 Eur/kWh) and have a life time of 2,200 (full) cycles (Kempton, 2000). This results in cost for battery usage of around 0.05 Eur/kWh per cycle. Other storage cost assessments from (Chen et al., 2009) consider costs to be in the range of 0.15-1.00 USD/kWh per cycle (0.11 - 0.74 Eur/kWh p.C.), which is a rather high spread. More recent work by Peterson et al. (2010) proposes values of 0.042 USD/kWh (0.03 Eur/kWh) at the low end of the spectrum of battery degradation costs. In order to obtain a more robust assessment three different energy degradation cost levels are used in the following analysis: 0.05, 0.1 and 0.2 Eur/kWh.

Table 4.8: Average weekly costs per vehicle in Euro.

	Employees			**Retired**		
	AFAP	Smart	V2G	AFAP	Smart	V2G
11 kW charging power						
No Degradation Costs	6.00	3.99	2.18	3.94	1.88	-0.36
ψ_{en} = 0.05, β_{cr} = 0.01	7.76	5.46	4.70	5.07	2.48	1.27
ψ_{en} = 0.1, β_{cr} = 0.01	9.47	6.42	5.23	6.19	3.04	2.38
ψ_{en} = 0.2, β_{cr} = 0.02	12.94	9.49	9.67	8.44	4.17	4.08
3.6 kW charging power						
No Degradation Costs	5.95	4.03	3.13	4.00	1.90	0.73
ψ_{en} = 0.05, β_{cr} = 0.01	7.72	5.42	5.40	5.16	2.47	2.05
ψ_{en} = 0.1, β_{cr} = 0.01	9.45	6.37	5.74	6.31	3.03	3.02
ψ_{en} = 0.2, β_{cr} = 0.02	12.94	9.41	9.88	8.62	4.16	4.39

4.3.5 Results - Savings from Smart Charging

In order to concentrate the analysis on the impact assessment of driving profiles and battery degradation costs on the economic outcome, the BMW Mini E is utilized as a reference vehicle with the driving profiles of the most contrasting sociodemographic groups: employees and retired persons. In addition, the available charging power is varied, incorporating the standard home socket outlets of 3.6 kW (one phase) and 11 kW (three phase) in Germany. This allows the analysis of the most distinctive groups in a realistic setting. As a considerable number of parameters is varied the reference scenario is further denoted to be the 11 kW case with the battery degradation parameters set to $\psi_{en} = 0.1$ EUR/kWh (energy-related degradation) and $\beta_{cr} = 0.01$ EUR/kWh (power-related degradation) for both groups.

Smart Charging reveals a considerable saving potential when compared to AFAP charging. Table 4.8 shows the average weekly costs for every charging strategy for both analyzed sociodemographic groups under consideration of different charging powers and battery degradation costs as well as infrastructure costs.[5]

Smart Charging enables savings for employees of at least 32% compared to AFAP charging. For retired persons in turn the relative savings are higher than 50% but the absolute costs per week and vehicle are not as high since the dis-

[5]Please observe that the full factorial of the parameter combination is simulated but only the main bounding scenarios are reported for better insight.

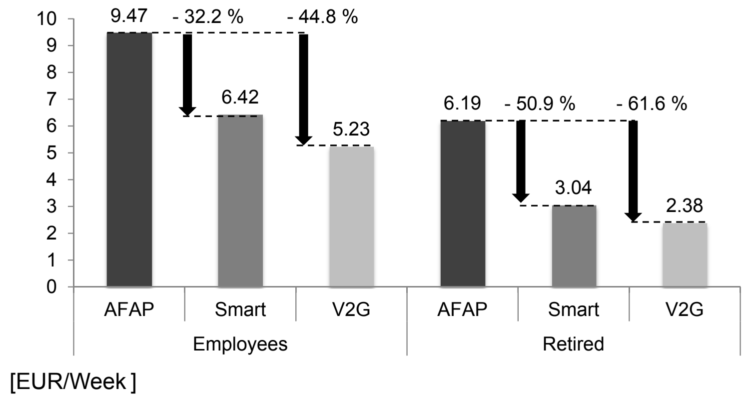


Figure 4.16: Weekly average cost savings including power and battery costs for the reference scenario with ψ_{en} = 0.1 EUR/kWh and β_{cr} = 0.01 EUR/kWh for the different charging strategies.

tances driven are considerably lower.[6] It can also be observed that if the battery degradation costs are included, the absolute costs per individual vehicle can more than double (from 6 to 12.94 EUR for AFAP and from 3.99 to 9.49 for Smart Charging) as compared to the theoretical no degradation case for employees.

Depending on the available charging power, the driving profile group and to some extent the battery degradation costs, the number of feasible profiles, i.e. profiles whose mobility needs are completely fulfilled slightly varies for each scenario. The cost values reported are thus average values per vehicle for the corresponding scenario population. In order to enable a consistent economic comparison the weighted average costs per vehicle for every charged kWh, split into energy and battery related costs for the reference scenario, are depicted in Figure 4.17.

It can be observed that for AFAP charging the energy costs are even higher than the yearly average (cf. Figure 4.14) cost of the variable pricing scheme, i.e. 0.175 EUR/kWh vs. 0.169 EUR/kWh, whereas the battery costs are not extensively higher than the energy degradation cost element. A lower charging power in the 3.6 kW case slightly lowers the average cost levels as it distributes some of the demand since it takes longer to charge a vehicle at this rate, which then occasionally includes more low price time slots than in the 11 kW case. AFAP is thus performing even poorer than a more evenly distributed average load charging strategy as it concentrates load every day in periods of high prices. Therefore, Smart Charging offers a substantial potential for cost reduction, even when the

[6]Employees have an average weekly driving distance of about 228 km whereas retirees only travel 119 km on average per week.

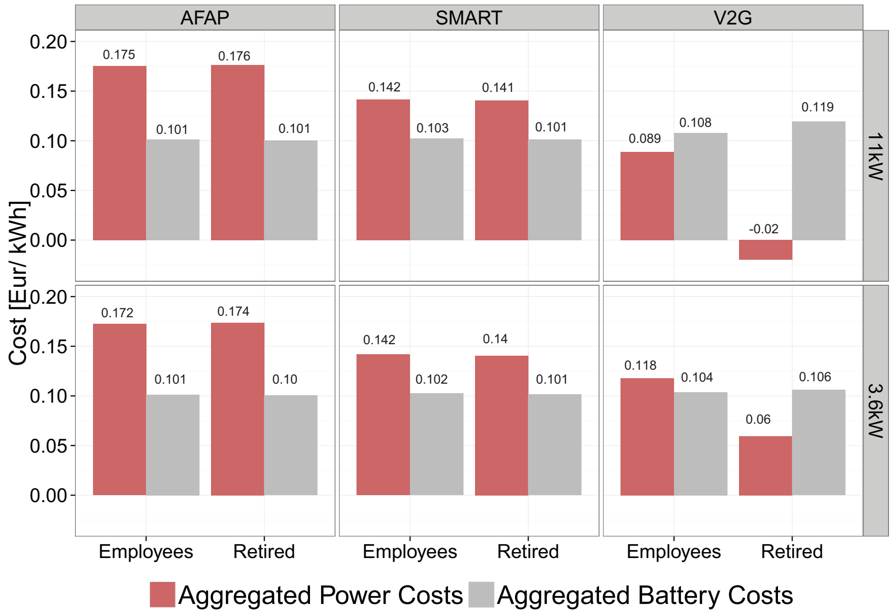


Figure 4.17: Effective energy costs including power and battery costs for the reference scenario for different charging strategies and powers.

underlying spread of the wholesale price is not that high when compared to the total electricity price.[7] Hence, the savings from Smart Charging are potentially higher as reported, since VAT proportionally increases the energy costs incurred, the absolute VAT payments are lower in the Smart Charging case. In order to allow for a consistent comparison with the costs of the V2G operation mode, a net cost assessment is performed.

4.3.6 Results - Revenue from Vehicle-to-Grid

The V2G charging strategy transforms the EV to a short term storage unit that performs wholesale energy price arbitrage, while still fulfilling the projected driving needs of the particular group. V2G can be particularly profitable as it further reduces costs in relation to Smart Charging, and even leads to profits when only the energy costs are considered. In particular the retirees can reduce their total cost by at least 49% (cf. Table 4.8 and Figure 4.17). Employees can further reduce their costs by V2G by at least 39% as compared to AFAP charging

[7]The overall charging amounts differ for AFAP as this charging strategy "overcharges" the battery to always have the highest SOC possible, whereas Smart and V2G only charge to 75% at the end of the week.

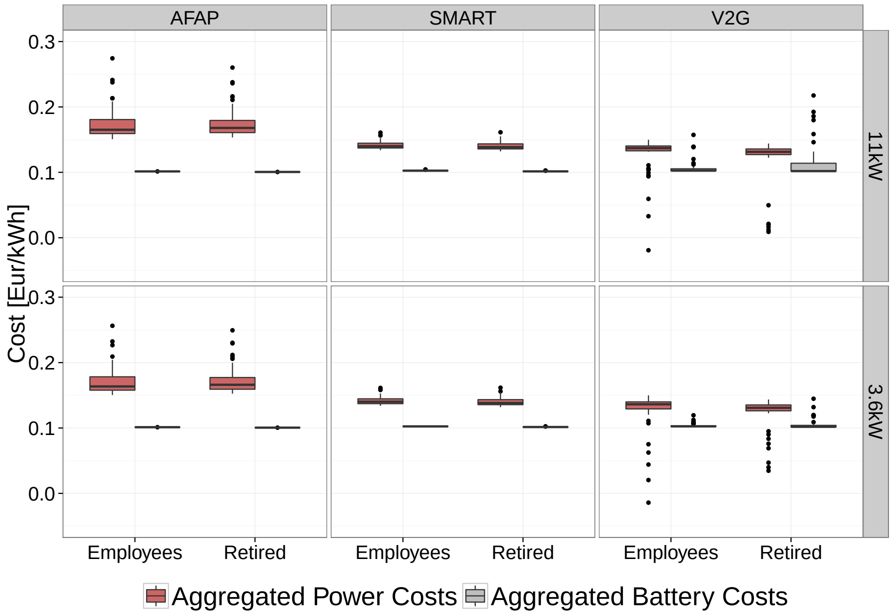


Figure 4.18: Battery and energy cost variation for the reference scenario in dependence of the charging strategy and charging power.

in the reference scenario.

In order to not only account for average price values but consider the dynamic cost variation per week, Figure 4.18 compares the weekly average costs for the different charging strategies. It can be observed that for AFAP the costs vary considerably in the direction of higher energy prices, whereas in the case of Smart Charging the cost variation is clearly confined. For V2G a similar energy price level is observed as with Smart Charging, but the deviations to lower, or in the case of retirees even to negative costs or profits can also clearly be seen. This is partly due to the fact that in autumn 2007 the wholesale energy prices reached considerably higher levels than most of the time before in this year. Battery costs in turn show the opposite deviation behavior, as V2G activity increases, they tend towards higher values. This is particularly the case for retirees that perform V2G in the 11 kW case. This also shows that a higher charging power enables the vehicles to generate higher profits as they can fully take advantage of high and low price time periods.

Figure 4.19 exemplifies the aggregate load of both groups for the course of two weeks (30 & 31, end of July) resulting from the different strategies. It can be seen that AFAP has a regular load pattern that particularly peaks in the evenings, but distributes the overall load such that the daily peaks can be lower than in the

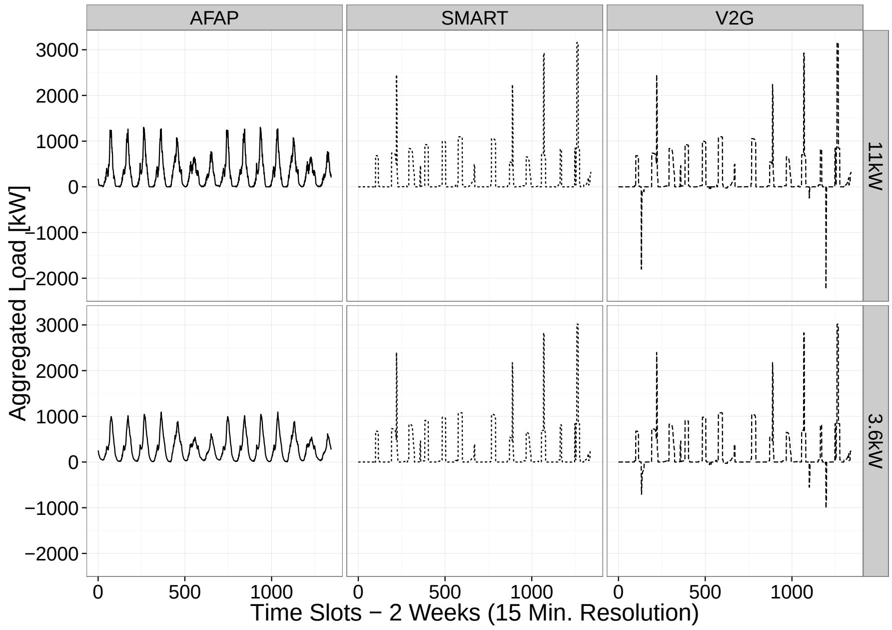


Figure 4.19: Exemplary aggregated load of both groups for the reference scenario during the course of week 30 and 31 for the different charging strategies.

Smart and V2G cases. Smart Charging has similar load levels of around 1 MW but can have higher coordinated peaks in order to take advantage of low price periods. The battery costs and in particular the power costs have a high impact on the aggregate charging load.

4.3.7 Results - Impact of Battery Degradation Costs

In order to not only account for operative electricity costs different levels of battery degradation costs associated with total energy throughput and the charging rate intensity are considered. These considerations notably change the nature of the overall economic outcome, as they can turn an operative profit in the V2G retiree case back into a cost position. If battery costs and in particular energy degradation costs are increased to 0.2 EUR/kWh, the battery costs even surpass the energy costs (Figure 4.17 and Table 4.8). For energy-related degradation costs of 0.05 EUR/kWh in turn the results show that operative V2G profits for retirees and battery costs compensate each other.

The C-rate and the associated quadratic power cost representation following the experimental evidence of Bashash et al. (2011) lead to considerably lower average charging powers per vehicle in the different cost value scenarios. Table

Table 4.9: Maximum average charging power per vehicle in kW.

11kW Ref. Case	**Employees**			**Retired**		
	AFAP	Smart	V2G	AFAP	Smart	V2G
No Degradation Costs	1.15	8.21	10.66	0.47	6.28	9.77
ψ_{en} = 0.1, β_{cr} = 0.01	1.15	3.73	7.28	0.47	2.57	7.83
ψ_{en} = 0.2, β_{cr} = 0.02	1.15	2.46	4.68	0.47	1.62	4.73

4.9 shows the average individual charging powers for the respective charging strategies.

AFAP charging has a very low average charging power as this number is averaged over the complete group of feasible profiles, but at the same time less vehicles are charging per time slot as compared to the other strategies. With no degradation costs, employees fully take advantage of the available connection power, but when C-rate costs are increased the average maximum charging power is considerably reduced from 8.21 kW to 3.73 kW and 2.46 kW respectively for no, medium and high power costs. The same holds in relative terms for retirees.

Figure 4.18 also indicates that energy-related battery degradation costs still remain the main determining factor for V2G activity at the given electricity price level. At the same time we can also observe that lower charging powers can support the implementation of V2G as they limit the amount of C-rate related battery degradation cost.

4.3.8 Conclusion

An individual economic optimization of charging times, minimizing the individual power and battery degradation costs allows to substantially reduce the overall costs of EVs by at least 32% for employees (from 9.47 to 6.42 EUR/Week) and at least 51% for retirees (from 5.07 to 2.48 Eur/Week) in the reference scenario when compared to the AFAP case. Electricity cost reductions under the assumed hourly variable rates can be realized with higher charging powers, but might be overcompensated by higher battery degradation costs and in particular power degradation costs in this case. A possible implementation of Smart Charging must thus account for this interrelation.

Performing V2G and thus discharging activities based on the wholesale energy price variations can be profitable in particular for retirees with higher charging and discharging power outlets. With low energy storage costs, this could even lead to profits while driving needs are fulfilled. Employees could reduce their total costs by 39%-45% on average per week as compared to AFAP, when participating in V2G activities. The analysis shows that an endogenous consideration of C-rate related costs leads to lower charging powers which can also be beneficial for EV power grid integration. In addition the energy storage costs still remain the main determinant for a profitable V2G implementation.

The analysis in this section also represents a benchmark for economic charging strategies under clear consideration of technical constraints. The dynamic rate represents the actual fluctuation of the wholesale price while eliminating tax and fixed fee effects on the charging decision. V2G is thus assessed under the current regulatory framework in which generators and storage devices are (partially) reimbursed their grid fee payments. Through the net cost approach the reported savings of Smart Charging might be underestimated as the VAT is calculated proportionally to the variable energy price. This shows that the regulatory framework is decisive for the assessment of different charging strategies. It can be concluded that V2G can be profitable, but like stationary storage devices might need additional regulatory incentives to represent a sustainable business case in power markets with decreasing wholesale price spreads like Germany.

Further work could consider shorter optimization horizons in order to account for price and trip uncertainty. In addition the 1:1 mapping of driving profiles to vehicles can be relaxed in order to account for EV fleet or car sharing scenarios. The implications of shorter optimization time horizons in conjunction with a variable and intermittent supply base will thus be investigated from the supply perspective in Chapter 5.

4.4 Discussion and Summary

Sections 4.2 and 4.3 investigated the potential of individual EV demand flexibility under similar assumptions but with slightly different input parameters. Both analyses incorporate the individual optimization perspective of an EV-owner that receives charging signals or in particular a dynamic price on a hourly basis and reacts in such a way as to achieve the given objective. The most prominent is the individual minimization of electricity costs for the resulting charging demand. Section 4.2 first focuses on an individual comparison of charging strategies that either aim to increase the average share of wind-power utilized for charging, minimize the system impact by charging during times of low system load (and thus load factor), or follow the already mentioned economic rationale of individual cost minimization.

Section 4.3 in turn focuses more on the individual economic implications if battery degradation costs are accounted for and additional Vehicle-to-Grid operation strategy is performed by the sociodemographic groups with the most contrasting driving patterns and thus charging demand requirements, being employees and retirees. The results show in both cases that a smart and in particular cost minimizing strategy can help to reduce individual electricity costs by at least 32%, with a potential of up to 77% as compared to the uncoordinated AFAP strategy. Other objectives like the increased utilization of wind-power can also be fulfilled effectively. A more detailed discussion and comparison in the next paragraphs supports the notion that smart charging *is* indeed worthwhile.

Renewable Energy Utilization and Grid Implications

The charging strategies in Section 4.2 encompass four coordinated charging approaches. The strategies aim to maximize the average wind-share they use for charging on a system scale (*WL*), minimize the system load factor during their charging time (*LF*), minimize their system impact while reacting to the availability of wind-power (*Residual*) and minimize their individual costs (*EEX*), respectively. The last economically-centered strategy is also evaluated in Section 4.3 with the extension to sell energy back to the power grid, while still fulfilling mobility requirements. The individual evaluation shows that the *WL* strategy can double the relative wind share that is employed for charging for employees and retirees the like. It can increase the adopted share from 7.43% to 14.72% for employees and from 7.51% to 15.57% for retirees. The costs it incurs with around 4.31 EUR per week for employees (2.25 EUR for retirees) is only about half the weekly costs of AFAP, but nearly double as much than in the cost optimal *EEX* strategy. The additional wind share thus comes at a higher price under these conditions. As the share of renewable power increases continuously in Germany, so will the average share; but the evaluation shows that additional coordination can substantially contribute to make EVs more sustainable on an operative basis. The individual reaction of rational and price responsive EV-owners can also be detrimental to distribution grid equipment if only global system capacity constraints are considered. Nevertheless, the evaluation of the different charging strategies allows for a good assessment of the effect of different coordination objectives.

The *LF* and *Residual* charging strategy address the technological constraints on a system level. They both aim to charge at times when system load is low.

This leads to a concentration of charging during the nighttime and in particular on Sunday mornings, since this is typically the time with the lowest load in the system in regular weeks. *LF* charging thus resembles more a classical night-charging strategy, while it takes advantage of the demand flexibility of EVs and does not need to charge every night. The *Residual* strategy in turn distributes its charging times predominantly to times when the residual load is low. This can either be the case at times of high wind-power feed-in and specifically addresses situations of low load and high wind-power generation which can be critical for the power grid. Since the share of volatile generators is increasing, this strategy provides a possibility to utilize the demand flexibility of EVs to take advantage of possible excess wind generation while helping to stabilize the overall system. The overall effect of the *Residual* strategy though is still essentially coined by the regional distribution and in particular the number of responsive EVs in the power system.

With respect to their wind power utilization *LF* and *Residual* are quite different. *LF* only achieves an average share of 9.92% (10.50%) for employees (retirees). *Residual* in turn achieves 11.89% (12.13%) for employees (retirees), a remarkably higher value even though the costs per week (and per kWh) are nearly similar with 3.04 (0.08) for *LF* and 3.03 (0.08) for *Residual*. This individual evaluation thus shows that the *Residual* strategy is a promising alternative. It considers the overall system load and at the same time the availability of renewable electricity sources at a lower cost level than the wind centered charging strategy. In order to account for the interrelation with the V2G strategy, the cost minimizing *EEX* strategy will be discussed in the next paragraph.

The utilization of empirical driving profiles enables a realistic assessment of the charging demand requirements resulting in a specific area, which can be helpful for a more technologically focused analysis. The main differences between employees and retirees consist in their differing energy requirements, but also in their availability at the home charging location. This can have interesting implications for charging strategies that seek to take advantage of the respective demand flexibility. The analyses in this chapter only assumed charging at the home location of the EV, the resulting uncoordinated load patterns show that the charging of retirees is more distributed over the day while it is more concentrated in the evening hours for employees (cf. Figure 4.13). This demonstrates that while retirees have a higher charging time flexibility and a higher potential availability at grid connection points, employees have a higher demand flexibility since they need more electricity for their driving. Employees are thus a more constantly available flexible load, which at times of connections does not have the temporal flexibility as retirees have. Chapter 5 further investigates this relation with respect to the adoption of renewable energy. Further, more abstracting analyses with respect to flexibility and its formalization can be found in Stroehle et al. (2012).

Individual Economic Evaluation and Implications of V2G

The individual economic evaluation that is undertaken in the previous section shows that, given a dynamic hourly pricing scheme that maps the price volatility of the wholesale market, the ability to respond can be very beneficial for every EV-owner. The main assumptions here are that such kind of rates are available to end customers and that the bulk of the remaining demand stays inflexible such that no significant demand shifting occurs that would affect the price formation process. For the first years of EV availability the share of EVs on total load in Germany will remain negligible, which supports this economic aspect of the cost minimizing strategies.

The main input data and the analysis frame (i.e. the driving profiles and the EV specifications) are similar for Section 4.2 and 4.3. The price input data is also similar (EEX data from 2007), but is scaled differently. This enables only a general comparison and shows the relevance of valid assumptions about the development of the respective market parameters. Both analyses followed the idea that EV-owners as private entities will pay the average household rate for the respective year. The first implementation in Section 4.2 linearly scales the EEX intraday price to a level of 20.01 ct/kWh. This calculation implicitly assumes that taxes and regulated fees also scale with the same rate as the generation price does. Since in reality the electricity price for end-customers is still highly determined by regulated price components, the analysis in Section 4.3 only assumes that the wholesale component is volatile, and adds a fixed amount for fees and energy taxes. In addition the VAT is omitted in the second analysis in order to allow for a consistent cost comparison in the case of the V2G strategy. Overall the resulting individual cost values can not be simply compared but nevertheless an assessment of relative savings and general tendencies can be performed.

The overall *average* cost level for employees in the first analysis is 2.32 EUR per week and 0.067 EUR per kWh. In the second analysis the respective cost for no battery degradation (the corresponding case) are 3.99 EUR per week and 0.138 EUR per kWh. The respective costs for retirees are 1.14 EUR per week (0.062 EUR per kWh) and 1.88 EUR per week (0.138 EUR per kWh). Since the charging times are nearly the same the resulting deviation between the two approaches mainly

Table 4.10: Storage cost comparison between simple linear cost based and endogenously defined values in EUR per week.

11 kW Ref. Case	**Employees**			**Retirees**		
Storage Costs (EUR/kWh)	AFAP	Smart	V2G	AFAP	Smart	V2G
Endogenous (0.1/0.01)	3.47	2.43	3.05	2.25	1.16	2.74
Endogenous (0.2/0.02)	6.94	5.50	7.49	4.50	2.29	4.44
Exogenous Linear (0.1)	3.44		-	1.83		-
Exogenous Linear (0.2)	6.89		-	3.65		-

comes from the different scaling approach. For employees, the difference in the average costs per week and per kWh is 71.92% and more than 100% respectively. This shows the high sensitivity of the approach with respect to the variable price inputs. The first analysis is more likely to overemphasize the variation of the wholesale power price. Since the scaling encompassed all components of the power price, this first approach is prone of overestimating the spreads that are occurring on the end consumer level. The second analysis in turn is more accurate in this sense, as the volatile components are smaller which in turn leads to a higher average price level (as can be seen in the respective kWh price), but a less accentuated peak price level. This can be observed as the AFAP price level in the second case is lower at 6.00 EUR per week (employees) as compared to 8.42 EUR per week. Taken together it can be observed that the approach from Section 4.3 more accurately represents the current situation in the German power market, while the approach in Section 4.2 enables a general characterization of the different charging strategies.

Storage cost considerations are very important when it comes to the assessment of charging strategies. In particular when a more active role of EVs in a V2G operation strategy is pursued these parameters are the main determinants of economic potentials. Storage costs were not considered in the initial analysis, but a simplified linear cost assumption supported the assessment of the operative savings achieved by the different strategies in the correct context. The second analysis in turn made the storage cost an endogenous part of the modeling approach. The model can thus account for battery degradation resulting from energy throughput (similar to, but not equal to the previous DoD considerations) and charging power related degradation. These assumptions follows evidence that higher charging powers are also detrimental to battery life time.

Table 4.10 provides a comparison between the basic linear storage cost assumptions from Section 4.2 and the endogenously defined storage costs for similar cost parameters from 4.3. It can be seen that for the reference 11 kW charging power case the linear storage costs and the endogenous cost are quite similar for AFAP with 3.44 EUR per Week as compared to 3.47 EUR per week (0.1 EUR per kWh energy related storage costs for employees). When the values are compared for Smart Charging it can be seen that the values differ substantially. To a small extent this is due to the assumptions about the terminal weekly SOC values of the vehicles, which lead to an overall slightly lower energy throughput value for Smart Charging. As the driving profiles and the consumption values are similar, this example shows that endogenously modeled battery costs can improve the robustness of the economic results and enable a more reliable assessment of the individual value of charging coordination.[8] For retirees the cost deviations between the two cost modeling approaches is substantial, which shows that linear approximations, even when based on similar assumptions about energy throughput, are only a starting point for an accurate economic assessment of storage costs for EVs.

In conclusion it can be said that storage costs are clearly driven by the respective charging strategy of the EV, in particular it can be observed that higher charging powers enable EV-owners to take advantage of the low price time intervals. On the other hand higher charging powers are not always necessary to fully take advantage of the economically beneficial time slots. This is due to the fact that accurate trip and thus energy requirement information enable the EV to shift its charging times in such a way that battery degradation costs are minimized while mobility requirements are met. Following a V2G strategy based on the wholesale market prices reduces the electricity costs or, in the case of retirees even generates profits, if storage costs are lower than 0.05 EUR per kWh. Since the assumptions under which the respective scenarios were investigated shape the nature of the results, the main shortcomings and possible further extensions of the analyses are discussed in the next paragraph.

Critique and Further Research Opportunities

Both analyses presented in this chapter can be regarded as an upper case benchmark with respect to the objectives of the different charging strategies. This is mainly due to the assumption that trip, price, and renewable generation information are available one week in advance. The incorporation of shorter opti-

[8] Please observe that for lower charging powers and in the case of the V2G strategy storage costs also vary in the case of endogenous storage costs since the costs also depend on the charging power applied by the vehicle.

mization horizons is likely to deliver results that do not attain the same cost reduction or renewable energy utilization share as presented and discussed above. On the other hand one must also consider that wholesale market prices which are used above are well known and fixed in a day-ahead process in the German electricity system. In addition many trip patterns, for instance of employees are also fairly regular (e.g. trips to work and back), which suggests that the main tendencies with respect to the individual economic implications or renewable energy adoption rates are still valid. In Chapter 5 a shorter optimization horizon will be investigated with a focus on its effect on the integration potential of renewable energy in the charging demand of similar fleets as scrutinized above.

The demand patterns presented above in Section 4.2 can be problematic for the power grid infrastructure on the distribution level if the EVs are concentrated in a particular region. As was shown in Section 4.3 the reduction of individual charging power can be a solution to this problem which has the benefit that it can reduce power-related battery degradation costs. Information about trip requirements is thus key to enable the EV to determine a charging schedule that reduces grid impact and increases battery life. Further work could employ additional local grid capacity signals in order to allow for an economically efficient allocation of resources in this context. A possible approach is presented in Flath et al. (2013).

The following chapter will address the supply side perspective of EV charging coordination and further elaborate on the role of the EV aggregator and his possible optimization objectives.

Chapter 5

Supply Side Assessment

5.1 Introduction

After the individual evaluation of EV demand side flexibility and the resulting individual economic implications in Chapter 4, this chapter will address the perspective of the EV aggregator which has to supply his customer basis under different scenario assumptions. The aggregator needs to take decisions about which generation capacity from fluctuating renewable sources is needed in order to guarantee a sufficient supply of his customers. In order to satisfy the demand of his customers the aggregator can contract generators and in particular renewable generators with variable output (cf. Figure 5.1). In order to directly utilize the electricity delivered by his generators, he coordinates the flexible demand of the EVs in such a way that the net deviation between EV load and renewable generation is minimized. As the renewable generators are contracted for longer time periods (e.g., one year) there are times in which driving energy demand can not be postponed and thus requires a conventional generator as a back up solution in order to guarantee the mobility of the EV-owner.

The following sections will thus assess the overall ability of EVs in a given fleet scenario to directly utilize and thus balance the fluctuating renewable generation from wind and PV. In Section 5.2 a direct load control approach will be described which enables a general assessment of the flexibility of the given EV fleets. As this direct load control approach is not likely to be accepted by a majority of EV-owners, a decentralized, price based charging coordination mechanism is evaluated in a comparable setting with respect to the renewable energy adoption rates in Section 5.3. Other relevant impact factors that affect the charging time and spatial flexibility for charging such as charging powers and locations,

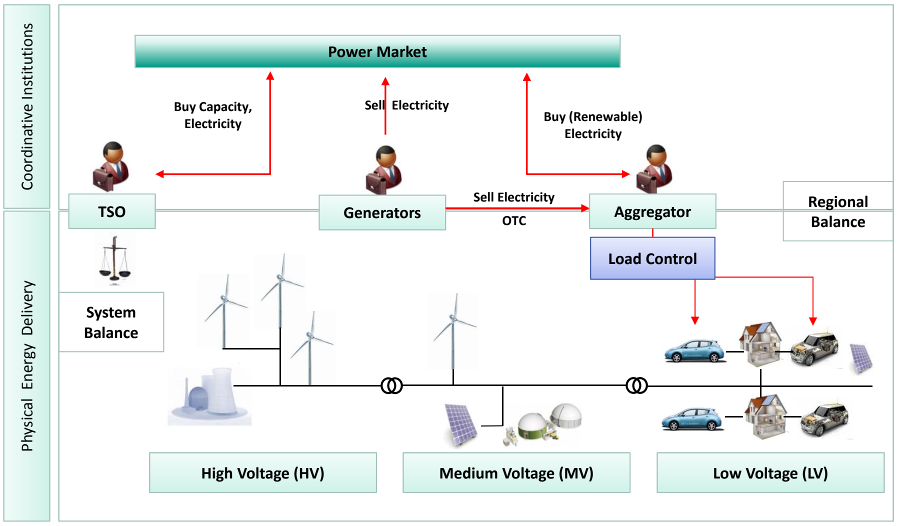


Figure 5.1: Analysis scenario overview for the optimal benchmark case.

different generation patterns, and combinations of fluctuating sources as well as the driving profile properties are investigated in both scenarios. The following sections thus expand the economic focus of Chapter 4 by a predominantly technical evaluation of EV demand flexibility.

5.2 Renewable Energy Integration: Optimum Benchmark Model

In order to assess the potential of EVs to adapt their charging demand according to a given variable and intermittent generation source a scheduling based centralized optimization approach is investigated in this section. This approach enables a basic comparison between the decentralized decisions performed in Section 4 and the theoretical optimum benchmark with respect to the direct utilization potential of renewable energy.

The scenario analyzed is based on similar data sets and assumptions as in the previous sections, and also emphasizes the supply side perspective of an EV-Fleet-Aggregator in charge of several hundred EVs and physical generation capacities. In this context the following research questions are addressed:

RQ 3 - Scheduling for Renewable Energy Utilization *Which share of renewable energy can be directly utilized by a fleet of EVs being scheduled according to differ-*

ent renewable generation patterns in comparison to an uncoordinated charging strategy?

RQ 3.1 - Source, Charging Power, Location Sensitivity: *Which effect do different portfolios of renewable sources, in particular wind and solar, charging powers and locations and driving profile characteristics have on the utilization ratio?*

RQ 3.2- Shorter Optimization Horizon: *What is the impact of a shorter optimization horizon with respect to the driving profile energy requirements and the utilization ratio of renewable energy?*

The analysis is considering an EV fleet of several hundred EVs with the same weekly empirical driving profiles of employees and retired persons employed in Chapter 4. In addition, it is assumed that the vehicles can be controlled in their charging behavior by an aggregator which covers their demand predominately from intermittent sources (i.e. wind and solar) and a conventional generator serving as a back-up to satisfy driving energy needs that can not be delayed. The aggregator has the objective to minimize the utilization of conventional generation in order to reduce his variable costs for energy provision. At the same time he is directly balancing intermittent resources which can contribute to a higher system stability and reduce CO2 emissions.

The model employed in this section partly builds on joint work from Gottwalt et al. (2013), but is evaluated in different settings and under consideration of additional parameters. The results obtained do not consider uncertainty about intermittent generation or trip occurrences. They represent a best case benchmark and thus a potential analysis for the employment of EV charging demand flexibility to map intermittent generation patterns. By reducing the optimization horizon to a daily schedule determination, the effect of less available information will also be addressed to assess the impact of more accurate information for longer time horizons.

Approaches addressing the direct control of EV charging with respect to the availability of intermittent resources have also been investigated by (Markel et al., 2009) and (Richstein et al., 2012). They either employ a direct renewable energy charging signal or a variable pricing scheme based on renewable energy availability. The renewable charging signal enables vehicles to reduce ramping requirements for renewable generation balancing, whereas the uniform pricing signal can lead to load concentrations but still allows for a higher adoption rate than in the uncoordinated case (cf. Section 5.3). Other scheduling based approaches with deferrable loads like thermostats show good utilization patterns of intermittent sources on a daily basis (Subramanian et al., 2012), but do not consider the special requirements of EVs. These analyses mostly demonstrate the general feasibility of charging coordination or assess decentralized charging decisions, but do not evaluate the ability of a fleet to balance a given generation profile. This investigation will be performed in the following paragraphs.

5.2.1 Model Input

In order to assess the potential of an EV fleet to adapt its demand according to an available renewable power source a centralized optimization approach, mapping the decision problem of an EV aggregator, is employed. For the analysis it is assumed that the generation patterns and the individual trips are known for the period of the optimization horizon. This makes the following model a benchmark assessment of the charging flexibility of an EV fleet in the given configuration. The optimization objective of the aggregator is to minimize the usage of conventional generation capacity by adapting EV charging to the given generation, but always under the condition that all trips are fulfilled, and hence the mobility needs of the drivers met. The technical implementation of the model builds on Java and the IBM ILOG CPLEX 12.4 optimization suite.

Driving Patterns

The driving behavior for the benchmark assessment is based on the previously employed profiles and sociodemographic groups, in particular the behavior of full-time employees and retired persons is modeled. The data set builds on the German Mobility Panel (MOP), as presented in Chapter 3. The profiles have a time resolution of 15 minutes which is also chosen as the time interval for the optimization process. The profiles have a time-horizon of one week. For the analysis the same most recent 1000 driving profiles for each group as in the analysis in Chapter 4 are utilized. Due to range restrictions of the specified EV some of the profiles can not be fulfilled. In addition, the restriction of charging only at the home location with the standard connection power of 3.6 kW also reduces the number of viable profiles. This represents a conservative approach to the assumption of charging infrastructure availability and will be addressed in more detail in the result section. When a profile is referred to as viable, this means that the profile can be fulfilled when charging takes place at the specified power level without delay after arriving at a location. This charging strategy thus corresponds to AFAP as introduced earlier. Any other controlled charging

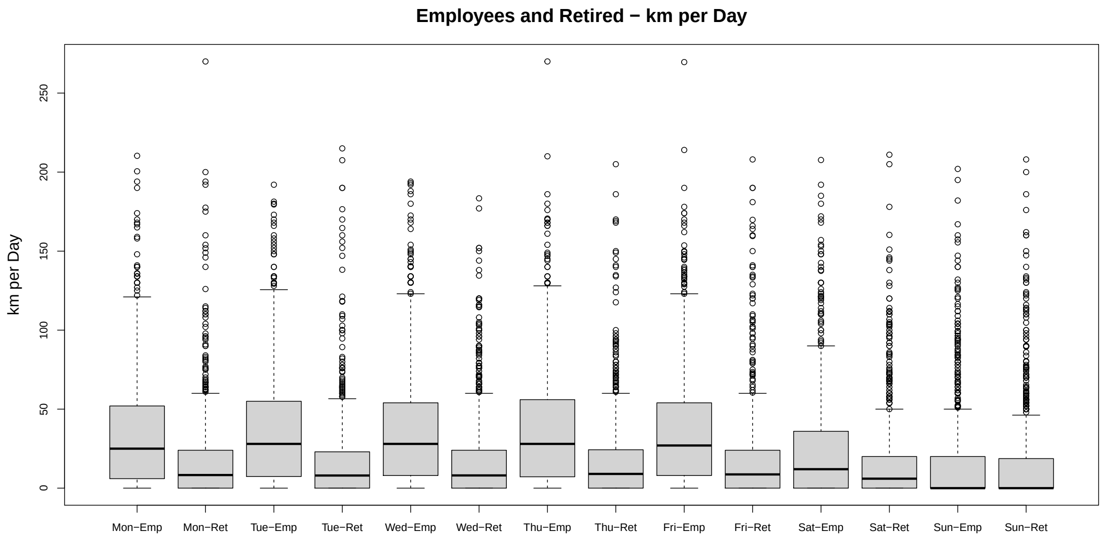


Figure 5.2: Weekly trip variation for employees and retired driving profiles.

strategy will likely encompass some delays, and will thus not charge the vehicle as fast, but instead will employ the flexibility for the given objective.

Because of the restrictions in battery capacity and charging power the following analyses are conducted with a sample of 846 vehicles of employees and 946 vehicles for retired persons in order to have the same data set in every scenario for comparison. This already shows that a vehicle with 31.5 kWh, even though it has quite a large battery can not cover all of the driving demand that occurs. Nevertheless, it can be observed that for employees still 846 out of 1000 initial profiles are viable, showing that for most purposes EVs are suitable. The direct comparison between retirees and employees shows that employees have very distinct driving needs, in particular on weekdays where most trips occur to work and back in the morning and in the evening respectively. Profiles of retired persons in turn have different patterns and beside their overall lower driving distance during a week also have their travel maxima during the day (cf. Section 4.3.2).

Figure 5.2 shows the range of variation of daily driving distances in km for both profile groups. It can be observed that the median of the daily driving distances of employees is 20.0 km on average over the whole week. On weekdays the median is 28.0 km whereas on weekends the median is only 6.0 km. This is a distinct drop in driving distance on the weekend. The mean values for employees are similar in their relation, on weekdays the mean distance per day is

36.8 km whereas on the weekend the mean distance is 20.5 km. There is a considerable amount of variation in the daily driving requirements for employees but 75% of the profiles travel less than 54.0 km a day demonstrating that EVs are very well applicable even to more demanding mobility requirements.

For the retired profile group similar general patterns can be observed for weekdays and weekends. The travel distances are considerably lower. The median for weekdays is only 8.05 km whereas the mean travel distance per weekday is 17.8 km. On weekends the variation is even higher, the median is 1.8 km and the mean 15.7 km. The 75% quantile with a value of only 22.0 km indicates, that the distance requirements of retired persons are less demanding than the ones of employees.

EV Specification

The EV specification builds on the values already presented in Section 4. The specifications are chosen such that they accurately represent current and near future vehicle technology. In particular the specifications similar to the BMW Mini E are (cf. Table 4.1) employed to characterize a generic EV. The usable battery capacity is 31.5 kWh and the consumption per km is 0.15 kWh, as specified in Table 5.3. This also enables a better comparison of the results obtained with respect to the required charging times and the applicability to the given empirical driving profiles. The charging powers that are assumed correspond to the basic capabilities of nearly every German household which allow charging in the range between 3.6 - 11 kW, following the specifications for EU Standard and EU Semi-Fast given in Table 2.6.

Generation Data

The renewable generation data was obtained from the 50 Hertz TSO in 15 minute resolution for the respective regulation zone consisting of eastern Germany and the city of Hamburg. This data was chosen in order to represent the already high share of volatile generation as compared to total load. For the utilized data set of the complete year of 2009 this means that the average minimum load of 4 - 5 GW during the night, could already be surpassed by wind generation with a generation maximum of 9 GW, (50-Hertz, 2010). The installed wind generation capacity of the 50 Hertz TSO-zone was 10,571 MW at the end of 2009, whereas photovoltaic (PV) generation only had an installed capacity of 975.1 MW. These two intermittent renewable energy sources represent the largest share of renewable generation capacity in Germany, are highly variable, and only to a minor

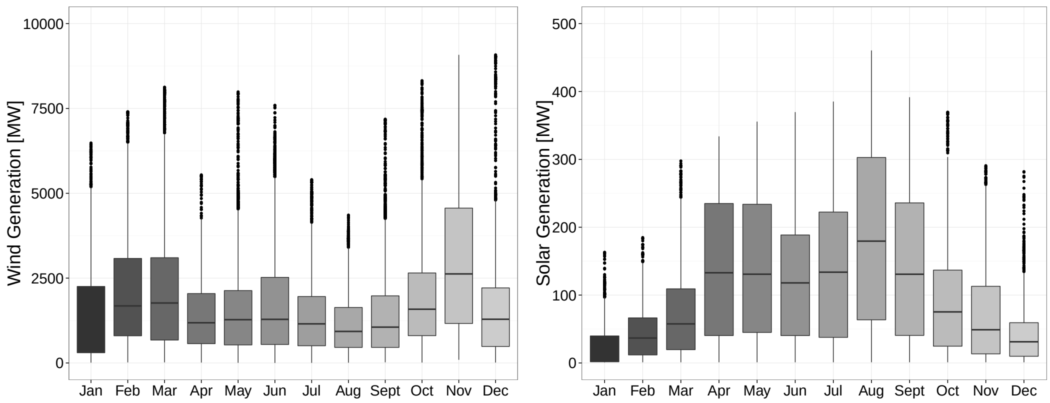


Figure 5.3: Monthly variation of the employed generation profiles for wind and PV in 2009.

Table 5.1: Summary statistics of the employed generation data.

Gen. Source	Min.	1st Qu.	Median	Mean	CV	3rd Qu.	Max.
Wind [MW]	1.2	555.4	1326.0	1789.0	0.91	2431.0	9081.0
Percent of Max. [%]	0.01	6.12	14.60	19.70	-	26.77	
Solar [MW]	1.0	22.8	80.3	111.5	0.92	182.8	460.5
Percent of Max. [%]	0.22	4.95	17.44	24.21	-	39.70	

extent controllable. Therefore, as argued before it is important to employ available demand flexibility for balancing purposes. Figure 5.3 shows the range of monthly generation variation for the complete year of 2009 for wind and solar generation.

It can be observed that wind generation has a typical higher overall production level in the winter and particular late autumn months. The variation level of wind generation is higher than the one of PV, even in relative terms. Table 5.1 presents the summary statistics of the generation time series for 2009. The minimal values are similarly low for both generation technologies, nevertheless, the difference between the generation maximum and the quantile and mean values is considerably higher for wind power than for PV. In particular, PV has a mean generation value (for the times with generation during the day) that is 4.13 times lower than the generation maximum. Both generation technologies show seasonal generation characteristics, e.g., wind is more prevalent in the winter and autumn months whereas PV has a clear overall maximum in the summer months.

Figure 5.4 shows weekly generation patterns of the data employed for the

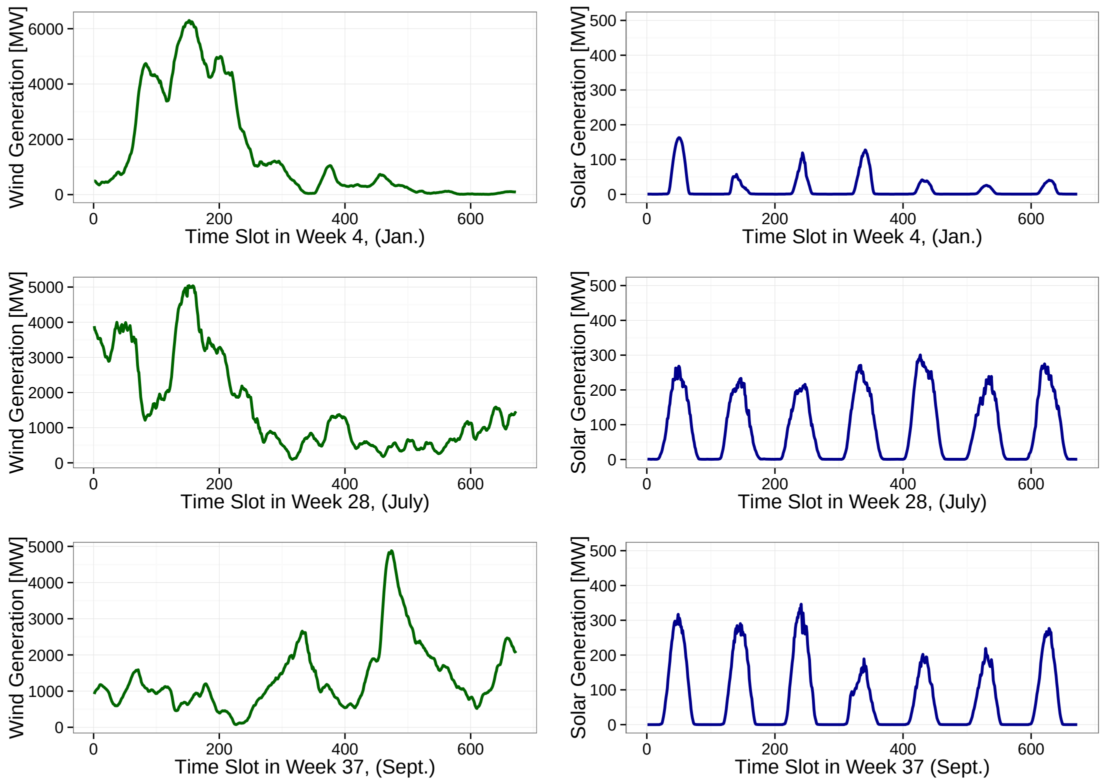


Figure 5.4: Exemplary weekly generation profiles for wind (left) and solar (right) generation for winter, summer and intermediate weeks.

analysis for winter, summer and intermediate periods. PV has as a clear diurnal cycle which makes it more predictable (on a large scale) than wind power generation, which in turn has no such clear cycles. The example of week 4 at the top of Figure 5.4 indicates that there can be periods in which wind and PV both do not generate sufficient energy for the projected energy needs of EVs for several consecutive days. Other examples in turn show that wind can be to some extent complementary to PV generation as in the case of week 37, where the generation peak occurs during a dip in the PV generation output. In order to still guarantee that the mobility requirements of the EV-owners are met, an additional controllable generator with minimum run time requirements is further assumed to cover this mandatory demand.

The renewable generation data presented above is rescaled in this analysis in order to map a hypothetical plant which is producing exactly as much electricity over the whole year as required by the respective EV fleet. This way the volatile characteristics of intermittent generation are represented by empirical

Table 5.2: Benchmark Model Parameters

Parameter Description	Symbol	Unit/Domain
Charge amount of vehicle v in time slot $[t-1,t]$	φ^{b}	(kWh)
Conventional generation in time slot $[t-1,t]$	$g_{t,C}$	(kWh)
Maximum generation in time slot $[t-1,t]$	$\overline{g_{t,C}}$	(kWh)
Renewable generation in time slot $[t-1,t]$	$g_{t,I}$	(kWh)
Number of time slots	T	15 min.
Number of vehicles	V	#
Consumption of vehicle v in time slot $[t-1,t]$	$d_{t,v}$	(kWh)
Battery state of vehicle v at time t	$SOC_{t,v}$	(kWh)
Usable capacity of the storage device	C	(kWh)
Maximum charge amount in one time slot	$\overline{\varphi}$	(kWh)
Charging efficiency	η^{c}	(%)
Charging availability vehicle v at time t	$z_{t,v}$	{0,1}

[b] please observe that in contrast to sections 4.2 and 5.3 φ is not only in the range [0..1] but characterizes an energy amount in kWh.

inputs and can be balanced by the coordinated demand of flexible EVs. The formal scheduling model that is important for the EV-fleet of an aggregator (cf. section 3.2) is therefore described in the next section.

5.2.2 Formal Description

The formal model in this section addresses the goal of an EV aggregator who seeks to minimize the variable costs for provision of electricity to a given fleet of EVs. This implies that for a given renewable generation profile the demand of the EVs needs to be distributed in such a way that the deviation between EV demand and renewable generation is minimized. In cases where renewable generation is not sufficient to fulfill the mobility energy requirements, a conventional generator with a minimum run time of one hour is employed to cover this demand. The time resolution of the simulation is 15 minutes and thus similar to the analyses in Section 4 and the resolution of the generation data. Further system dynamics within the 15 minute interval are not considered, all individual charging actions are uniformly distributed over this time frame.

The charging control performed by the aggregator can be formulated as a scheduling model that is minimizing the use of the conventional generation (cf. Equation 5.1), while all driving energy requirements and technical constraints of the vehicles and the generator are met. The model can be described as a mixed integer linear program with knowledge of future renewable generation and driving requirements over the time horizon:

$$\min_{\varphi, SOC, g_C, ramp, isOn} \sum_{t \in [1..T]} g_{t,C} \tag{5.1}$$

subject to the following constraints ($t \in [1..T], v \in [1..V]$):

$$g_{t,I} + g_{t,C} - \sum_{v \in [1..V]} \frac{\varphi_{t,v}}{\eta^c} \geq 0 \tag{5.2}$$

$$SOC_{t,v} = SOC_{t-1,v} + \varphi_{t,v} - d_{t,v} \tag{5.3}$$

$$0 \leq \varphi_{t,v} \leq z_{t,v} \cdot \overline{\varphi} \tag{5.4}$$

$$0 \leq SOC_{t,v} \leq \overline{C} \tag{5.5}$$

$$0.3 \cdot \overline{g_C} \cdot isOn_t \leq g_{t,C} \leq \overline{g_C} \cdot isOn_t \tag{5.6}$$

$$isOn_t \leq isOn_{t-1} + ramp_t \tag{5.7}$$

$$isOn_{t+i} \geq ramp_t \quad \forall \quad i \in \{1,2,3\} \tag{5.8}$$

$$isOn_1 \leq ramp_1 \tag{5.9}$$

$$SOC_{t,v},\ g_{t,C},\ \varphi_{t,v} \geq 0 \tag{5.10}$$

$$z_t, ramp_t, isOn_t \in \{0,1\} \tag{5.11}$$

The continuous decision variables are φ for the amount of energy charged in a time slot and g_C for the energy that needs to be delivered by conventional generation. The integer decision variables are *ramp*, which maps the ramping decision of the conventional generator and *isOn* for the description of the generator status in each time slot.

Constraint 5.2 ensures that generation (renewable and conventional) must cover the demand from EVs. Constraint 5.3 represents the fact that the SOC of each EV is determined by the energy level from the previous time step, the additional charging amount in the current period and the demand in this period (cf. parameter Table 5.2). Constraint 5.4 limits the charge amount per time slot according to the maximum amount allowed by the physical line limits. The next constraint (5.6) specifies that the conventional generation must be switched on to be operated at least at 30% of nameplate capacity and is not allowed to surpass this capacity, also implicitly determined by a maximum energy amount that can be generated per time slot. Constraint 5.5 maps the maximum capacity constraint for the individual battery. Constraints 5.7 and 5.8 account for the requirement of the conventional generation which has to be switched on in the last time slot if it is running in the current time slot. Otherwise it needs to be ramped, to be on in this time slot. Constraint 5.8 assures that the generator will stay switched on for another three time slots after being ramped. Constraint 5.9 secures that the conventional generation needs to be ramped in the first time slot. Finally constraints 5.10 and 5.11 account for the non-negativity and integrity requirements of the respective variables. The model presented in this section is thus a mixed-integer linear optimization problem that solves the variable cost minimization problem, given the empirical inputs specified above.

5.2.3 Results

The model was implemented and applied for 51 weeks of 2009 based on the specifications presented in Table 5.3 and the input data described above. In particular, the base case scenario is the simulation of 876 EVs with driving profiles of employees and 946 EVs with profiles of retired people respectively. These numbers represent the number of feasible profiles from the 1000 most recent driving profiles of the selected sociodemographic groups from the German Mobility panel (cf. Section 5.2.1). The standard charging power of 11 kW and (only) the home location are selected for the initial assessment with respect to the adoption capabilities for wind power of the vehicles. For employees an initial energy level of the battery of 20 kWh out of 31.5 kWh capacity and for the retired persons 10 kWh from 31.5 kWh capacity were employed for the analysis. These levels were selected to allow for a constant and more comparable number of vehicles to remain part of the benchmark solution when parameters were adapted in the sensitivity analysis performed below. In addition, these starting values enable to charge substantial energy amounts also at the beginning of every optimization period and thus avoid simulation artifacts while ensuring continuity over the weeks. As mentioned, the overall generation (wind, wind & solar, or only solar) is scaled to fit the overall demand over the entire analysis period, which is 51 weeks of 2009. This corresponds to the scenario of an aggregator which contracts one particular power plant for delivery over the period under investigation. The next paragraphs will first characterize the uncontrolled charging demand of the specified fleets and will then present the result obtained from coordinated charging.

Table 5.3: Base case specification of the weekly optimization problem.

Parameter	**Base Case**	**Unit**
Number of EVs - Employees	876	vehicles
Number of EVs - Retired	946	vehicles
Number of Time Slots	672	15-min. intervals
Battery Capacity	31.5	(kWh)
Charging Power	11	(kW)
Consumption	0.15	(kWh/km)
Initial SOC = End SOC	20/15/10[a]	(kWh)
Scale Renewable Generation	100	% of vehicle demand
Conventional Generation Capacity	240	(kW)
Charging Possible	Home location	
Generation Source	Wind power	

[a] The kWh values are different in cases with differing optimization horizons.

Uncoordinated Charging

Uncoordinated or as previously mentioned AFAP charging, serves as a reference case for assessing the impacts of optimal smart charging. AFAP charging only depends on the availability of charging infrastructure at a particular location, the driving profile and its travel distances. In the following analysis the charging locations home, work and leisure will be considered in order to map different levels of available charging opportunities. The base case specified in Table 5.3 encompasses only the most conservative assumption of charging at the home location of the individual EV. Further it is assumed that the EV is always plugged in at the time of arrival. In order to assess the general charging patterns resulting from the driving energy demand, the battery of the EVs is assumed to be fully charged in the AFAP case, as otherwise all vehicles would charge to the maximum capacity in the first time slots of the week.

Figure 5.5 shows the charging load resulting from AFAP for employees and retirees for the different charging locations for one week for the 11 kW case. It can be observed that employees have very distinct load peaks when returning back to their home in the afternoon and evening hours. During this time charging

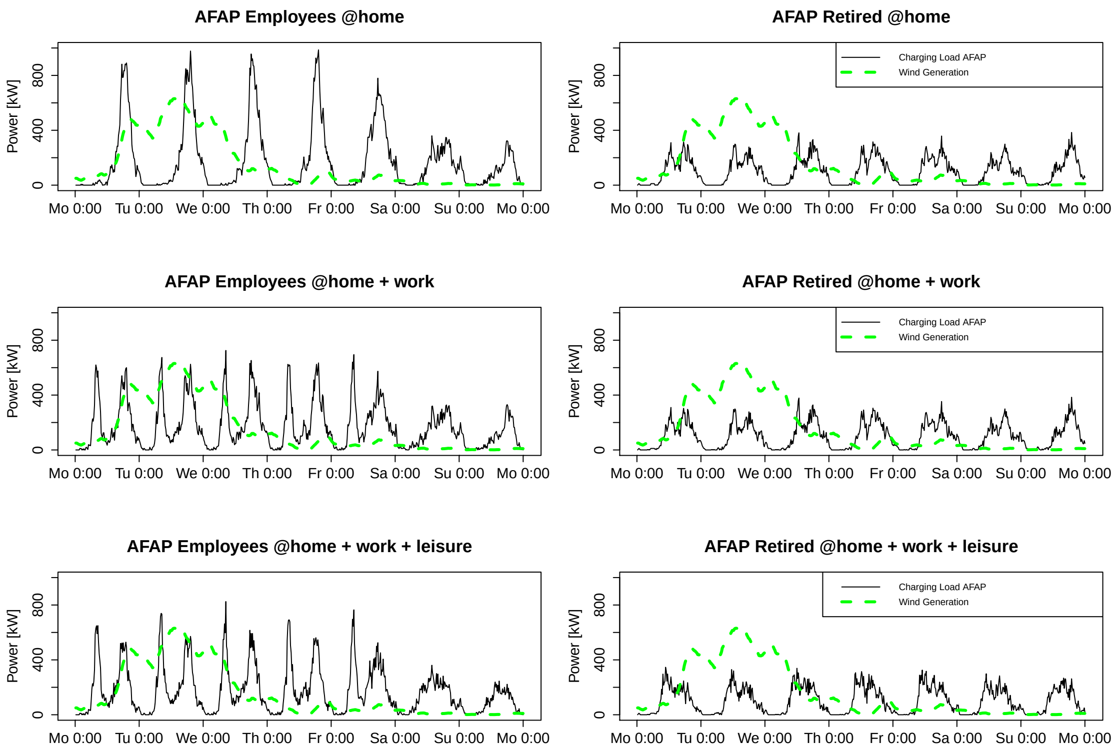


Figure 5.5: Charging load resulting from AFAP for employees and retirees with charging infrastructure at the home, work and leisure locations for the 11 kW base case with wind generation of week 4.

demand is highly concentrated. For retirees in contrast the charging demand is lower in absolute and also in relative terms. The trips of this group and thus the charging demand is more distributed during the day which leads to lower, and less distinguished peaks. Additional charging opportunities for employees at work redistribute their charging demand to two main, but overall lower, peaks which also has an impact on their potential ability to charge more renewable electricity from PV. Introducing charging opportunities at leisure locations does not notably change the load characteristics of both groups as compared to the home + work case. Interestingly it can be observed that a part of the retirees still have work trips in their driving profile.

With respect to the direct utilization potential of renewable energy through AFAP it can be observed, that the demand can fit by chance to the generation from volatile sources (wind power in Figure 5.5), and also depends on the availability of charging infrastructure at the respective location of the EV. Following the results described in more detail in the next section, AFAP can attain direct utilization rates of renewable energy between 41.24 - 45.37% over the analysis time horizon for employees in the depicted wind (only) case. Retirees in turn have a slightly higher utilization potential in the base case ranging from 49.27 - 52.86%. These values vary considerably with respect to the combination of renewable energy source employed for charging and the availability of charging opportunities.

Optimal Smart Charging

Optimal smart charging refers to the charging strategy that results from the solutions of the optimization problem formulated above in Section 5.2.2. This strategy results in a considerable increase in the share of utilized renewable energy in nearly all analyzed cases. For the base case of 11 kW home only charging with wind power as the only source, it can be observed that the yearly RES adoption share increases from 41.24% for AFAP to 84.00% for the optimal strategy for employees. For retirees one can see a similar result as the share of used renewable energy from wind increases from 49.27% for AFAP to 79.70% in the optimal case.

Figure 5.6 depicts the used share of renewable energy per week for AFAP and optimal charging for employees (left) and retirees (right) for every week of the analysis time frame of 51 weeks. In addition to the two sociodemographic groups also the different generation combinations are displayed. In particular an even mixture of wind and PV (in terms of energy provided over the whole year) and a PV only generator output are evaluated with respect to their utilization shares by the EVs.

For employees which use wind power for charging one can observe that there is a considerable number of weeks in which the complete driving energy demand is covered by this intermittent source. In week 26 in turn it can be seen that when there is shortage of supply at least 30% of the weekly demand is still covered from wind power in the optimal case. Retirees exhibit a similar general adoption pattern. For AFAP the general adoption level is higher which is mainly due to the longer availability times at the charging location and the more distributed demand pattern. For the second half of the year retirees show less explicit peaks in their wind power adoption per week as compared to employees. This can be explained by a lower overall wind production which in the first line leads to more conventional generation that is employed for charging. This in turn leads to a higher share of driving energy demand that is being covered by conventional generation due to the minimum run time constraints even though some parts could have been satisfied by wind power. Figure 5.7 (top) shows

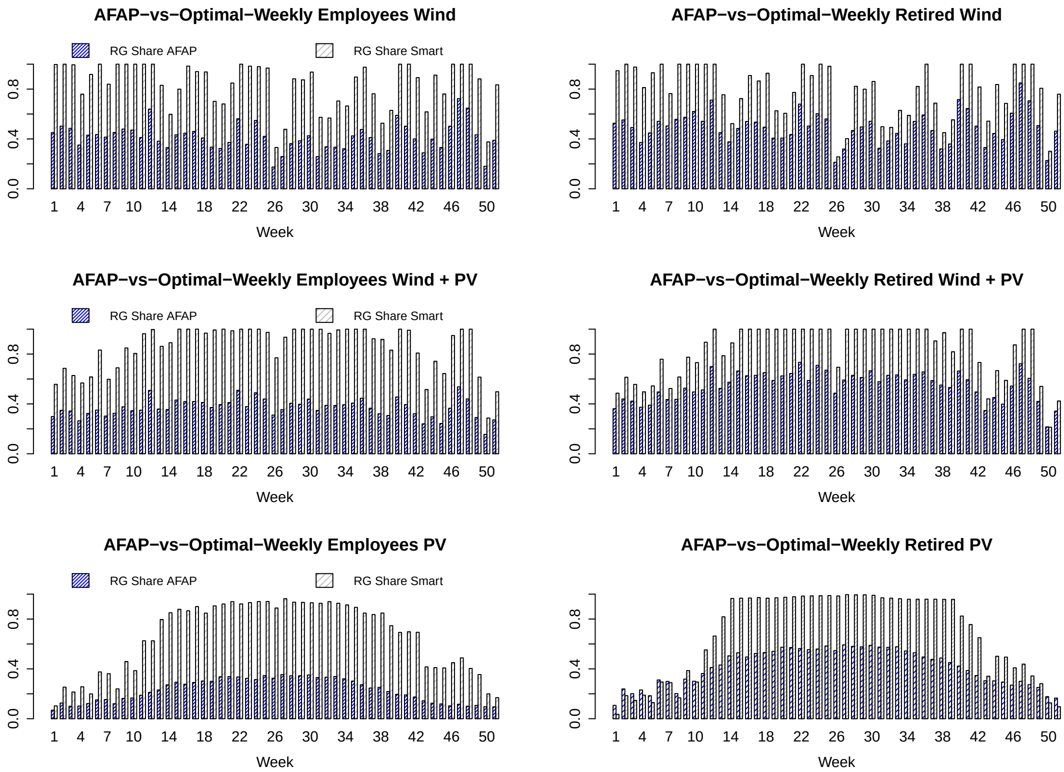


Figure 5.6: Renewable energy adoption share for Employees and Retirees for AFAP and the weekly optimization strategy for wind power (top), wind and PV (middle) and PV (bottom) for the 11 kW home charging base case.

the distinct conventional generation blocks that are supplemented in the respective week to fulfill the driving energy requirements. Please observe that the two groups are evaluated individually which in this case means that the generation is scaled to the overall yearly demand of the respective group.

When wind power and PV generation are evenly mixed for supply, the overall utilization of renewable energy is stabilized on a high level, with a yearly average of 85.95% of driving energy demand being covered for employees and 83.42% for retirees (cf. Figure 5.6). The AFAP values in this case are lower for employees (36.84%) and higher for retirees (54.88%) than in the wind power only case (cf. Table 5.4). The lower value for employees is due to the relative share of generation that now comes from PV at midday, a time when the employees are mostly not available to charge. The retirees in turn profit from this kind of generation and thus increase their share of utilized renewable energy in the uncontrolled case.

When only PV is used as a generation source, it can be observed that the value

Figure 5.7: Optimal smart charging load for Employees and Retirees in the weekly optimization vs. generation from wind power (top), wind and PV (middle) and PV (bottom) for the 11 kW home charging base case.

of the optimization is higher for employees which can use more than 80% of PV generation during the weeks with a more ample production pattern for the time from spring to autumn in the analysis time frame. The average utilization share over the complete period is still lower with 65.98% than in the wind power case. This is mainly due to the fact that employees are not at home when the daily production maximum occurs. Figure 5.7 depicts the smart load and generation patterns for a summer week (week 28, cf. generation patterns from Figure 5.4) and shows that employees predominantly charge in the shoulder times of PV generation but take full advantage of PV generation on the weekend. Retirees in turn can take advantage of PV generation every day and thus achieve a higher overall yearly value of 75.79% of their demand that is being covered. In the displayed week the conventional generation is not needed at all.

Table 5.4: Overview of RES average adoption shares for employees for the weekly optimization horizon depending on charging power, location and generation source compared to the corresponding AFAP values.

Employees Weekly	**Home**	**Home + Work**	**Home + Work + Leisure**	**Home**	**Home + Work**	**Home + Work + Leisure**
20 kWh		**AFAP**			**Smart**	
3.6 kW						
Wind	45.37%	52.45%	50.33%	83.70%	84.38%	84.38%
Wind + PV	37.37%	51.97%	55.10%	83.33%	86.96%	86.96%
PV	19.37%	35.20%	41.47%	61.30%	68.45%[a]	69.26%
7.2 kW						
Wind	42.22%	49.99%	48.73%	83.95%	84.36%	84.39%
Wind + PV	36.81%	49.93%	53.64%	85.38%	85.38%	86.96%
PV	21.54%	34.85%	41.33%	64.54%	72.60%	72.88%
11 kW						
Wind	41.24%	49.13%	48.20%	84.00%	84.40%	84.40%
Wind + PV	36.84%	49.34%	53.11%	85.98%	86.96%	86.96%
PV	22.60%	34.83%	41.03%	65.98%	72.75%	72.92%

[a] Please observe that this value was only obtained after the optimality level of the optimization was reduced to 90% as otherwise no valid solution was obtained with the available computational resources.

Sensitivity Analysis

Important factors for the ability to use renewable generation have been altered in the analysis in order to determine their impact on the results obtained. Besides the observations described above, the impact of varying charging powers, more charging locations the particular driving profile characteristics and the optimization horizon are discussed in this section.

For both analyzed groups three common charging powers were considered for the analysis. The charging powers range from 3.6 kW to 11 kW three phase outlet that is employed for residential and other, i.e. public charging locations in Germany. Table 5.4 and 5.5 provide an overview of the optimal and AFAP average utilization shares for the mentioned charging powers. For the base case and the optimal charging strategy no significant change in the average yearly value can be observed for employees and retirees. For the AFAP base case one can see that lower charging powers lead to a slightly better utilization rate of wind power as the vehicles charge for longer time intervals which potentially have a higher availability of renewable power. This observation is similar for all charging locations.

In addition to the charging power, the provision of additional charging op-

Table 5.5: Overview of RES average adoption shares for retirees for the weekly optimization horizon depending on charging power, location and generation source compared to the corresponding AFAP values.

Retired Weekly	**Home**	**Home + Work**	**Home + Work + Leisure**	**Home**	**Home + Work**	**Home + Work + Leisure**
10 kWh		**AFAP**			**Smart**	
3.6 kW						
Wind	52.86%	53.22%	50.55%	79.69%	79.70%	79.71%
Wind + PV	55.75%	56.29%	64.22%	83.42%	83.42%	83.42%
PV	38.88%	39.34%	52.49%	63.19%[b]	64.91%	66.32%
7.2 kW						
Wind	50.22%	50.66%	49.09%	79.70%	79.70%	79.71%
Wind + PV	55.04%	55.64%	64.12%	83.42%	83.42%	83.42%
PV	40.78%	41.01%	53.85%	67.11%[b]	72.57%	72.84%
11 kW						
Wind	49.27%	49.71%	48.52%	79.70%	79.70%	79.71%
Wind + PV	54.88%	55.47%	63.79%	83.42%	83.42%	83.42%
PV	41.59%	41.83%	54.21%	68.12%[b]	72.68%	72.84%

[b] Please observe that these values were only obtained after the optimality level of the optimization was reduced to 95% as otherwise no valid solution was obtained with the available computational resources.

portunities was also part of the performed analysis. The base case location (home) is complemented by additional charging opportunities at the work location, which is most relevant for employees, and by charging at leisure locations (e.g. restaurants). Together the charging opportunities cover most of the currently envisioned locations for public and commercial charging infrastructure. Additional charging infrastructure at work locations only slightly increases the utilized share of wind power and the mixed portfolio for employees. For the PV only case the additional charging opportunity notably increases the utilized share from 65.98% in the base case to 72.92% in the home + work + leisure case. The number of charging locations is not as important for retirees, but has a higher relevance for employees in particular when PV generation is to be employed for charging. The relevance of additional locations increases again if a shorter optimization time horizon is considered, as more charging options increase the intraday flexibility and optimization potential. This is now analyzed in more depth in the following paragraphs.

Impact of a Shorter Optimization Horizon

The reduction of the optimization horizon has a substantial impact on the results obtained for both groups. The look-ahead horizon of one week is mainly determined by the documentation frame of the empirical driving profiles. This look-ahead period for the optimization is now adapted to one day. For this time frame the assumptions regarding the availability of information about trips and generation profiles are equal to the weekly analysis. This means in particular that during the day there is no insecurity about the driving events and the generation from renewable sources. This represents real life conditions only to a certain extent, but already incorporates considerably less assumptions about the information that would be needed for a complete week. In addition, the reduction to a daily optimization horizon is common for optimization problems that employ the variable day-ahead prices from the respective wholesale markets as one of their main economic inputs. The day-ahead optimization can thus better account for the planing uncertainty with regard to trips and in particular with respect to volatile renewable generation as the week-ahead optimization. Trips are very likely to be known one day in advance, even though there is always a probability for spontaneous mobility requirements. Generation forecasts are also substantially better for shorter time horizons. The following results thus show what particular impacts result from the reduction of the optimization horizon.

Figure 5.8 shows the share of renewable energy used by employees (left) and retirees (right) in every week of the analysis time frame, again in comparison to the AFAP strategy in the 11 kW home charging base case. It can be observed that optimal charging increases the share of renewable energy utilized for every one of the three generation portfolios. Nevertheless, there is a notable difference between the daily- and weekly-optimization average values. In particular, the mean utilized renewable energy share over the year in the wind generation case is reduced from 84% to 62.78% (cf. Table 5.6). The AFAP values in turn do not change since the charging behavior is not altered to respond to additional constraints.

For retirees the situation is similar in the wind generation case, the optimal yearly average utilization values in the daily optimization only reach 64.37% vs. 79.70% (cf. Table 5.7). The value in terms of the improvements enabled by the optimization under the specified assumptions is thus decreasing if less information about future trips is available. This substantially reduces the flexibility potential of EVs as a controllable load in the context of renewable energy integration. More regular generation patterns during the day increase the utilization

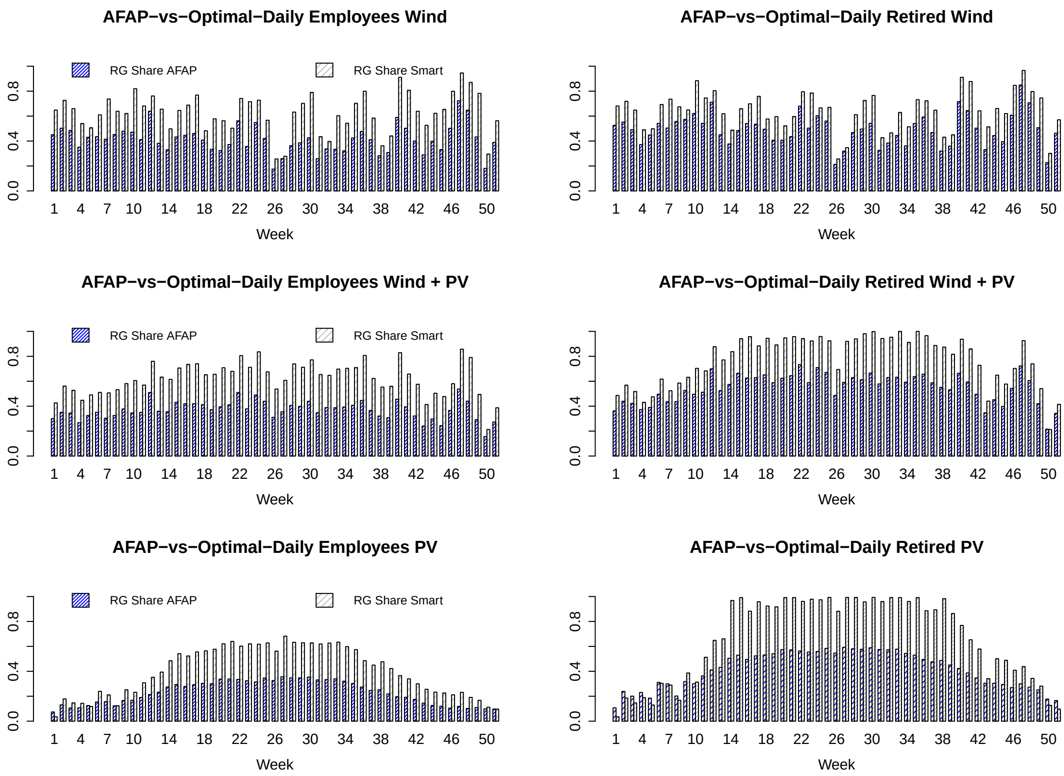


Figure 5.8: Renewable energy adoption share for Employees and Retirees for AFAP and the daily optimization strategy for wind power (top), wind and PV (middle) and PV (bottom) for the 11 kW home charging base case.

level of renewable energy both for employees and retirees as compared to AFAP, which can be seen for the generation portfolios incorporating PV. The utilization share in the optimal case for wind and PV generation with 62.29% is still lower than for the weekly optimization with a value of 85.58%. For PV the increase is more prominent, but also lower than in the weekly optimization frame. Overall it can be observed that retirees can again take better advantage of the intermittent generation and in particular PV. The reduction of the optimization horizon is reducing the load flexibility of EVs, but in particular the one of employees which are now more constrained with respect to their possible charging times and thus charge more often as it is necessary in the longer optimization time horizon.

Figure 5.9 shows the smart charging load of employees (left) and retirees (right) in conjunction with the respective renewable and conventional generation source for the same summer week as discussed above (week 28). For employees in the wind generation only case it can be seen that the conventional generator is used more frequently in order to cover the demand resulting from

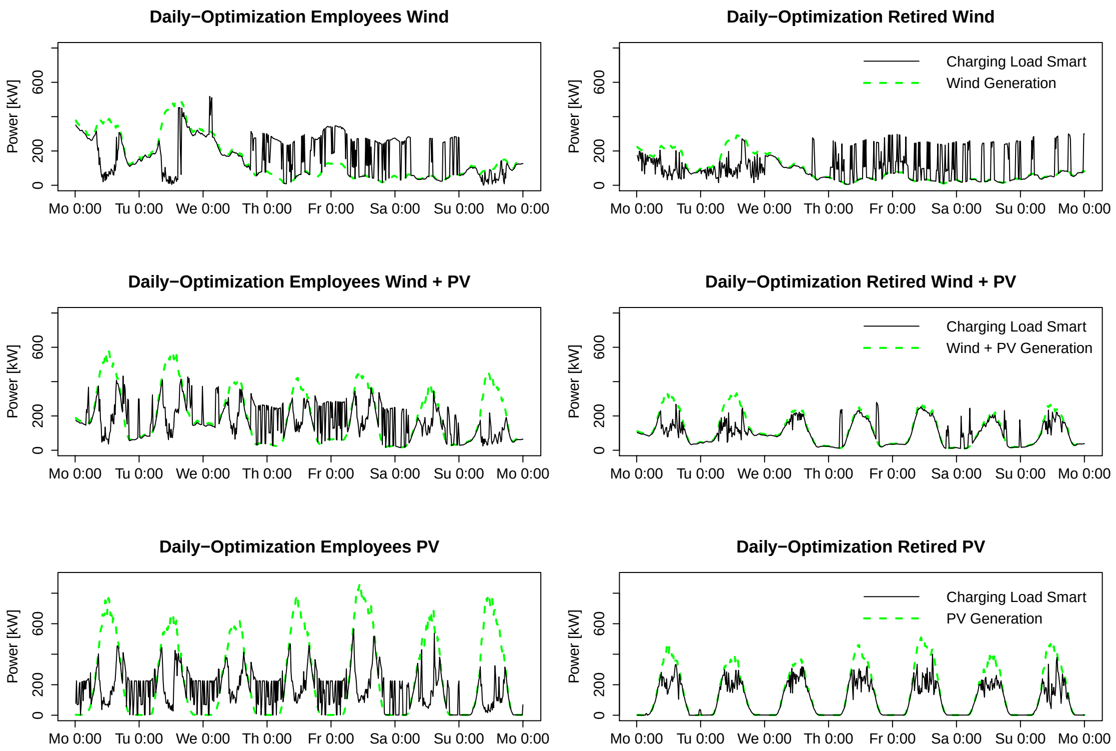


Figure 5.9: Optimal smart charging load for Employees and Retirees in the daily optimization vs. generation from wind power (top), wind and PV (middle) and PV (bottom) for the 11 kW home charging base case.

the daily charging cycles, in particular in the second half of the week. For retirees a similar pattern depicting the minimum run time requirements of the generator, can be observed. For generation portfolios with more PV one can see that the share of conventional generation increases during the night, but decreases during the day. This is very distinctive in the case of retirees that only use PV as a source. In this particular scenario almost no conventional generation is needed anymore. For employees in turn the conventional generator is only used during the night in this scenario. This also leads to the fact that employees charge more from the conventional generator in order to fulfill the run time requirements and thus have less demand that can be covered by PV. In addition, the battery energy level constraints that need to be met also lead to a higher utilization of the conventional generator.

For the daily optimization one can observe similar impact directions of increasing charging powers. For AFAP higher charging powers reduce the utilized share of renewable energy for both groups since charging is performed

Table 5.6: Overview of RES average adoption shares for employees for the daily optimization horizon depending on charging power, location and generation source compared to the corresponding AFAP values.

Employees Daily	**Home**	**Home + Work**	**Home + Work + Leisure**	**Home**	**Home + Work**	**Home + Work + Leisure**
15 kWh		**AFAP**			**Smart**	
3.6 kW						
Wind	45.37%	52.45%	50.33%	62.54%	63.45%	63.14%
Wind + PV	37.45%	52.04%	55.16%	59.43%	73.95%	74.08%
PV	19.37%	34.81%	41.47%	33.86%	63.09%	64.50%
7.2 kW						
Wind	42.22%	49.99%	48.73%	63.02%	63.45%	63.14%
Wind + PV	36.87%	49.99%	53.69%	61.16%	73.95%	74.08%[c]
PV	21.73%	35.08%	41.54%	38.17%	64.81%	64.93%
11 kW						
Wind	41.24%	49.13%	48.20%	62.78%	63.14%	63.14%
Wind + PV	36.90%	49.40%	53.16%	62.29%	74.08%	74.08%
PV	22.77%	35.04%	41.23%	40.11%	64.60%	65.00%

[c] Please observe that the optimal result numbers are rounded for the sake of clarity. This leads to the fact that the slight differences in the numerical values are not apparent in this table.

Table 5.7: Overview of RES average adoption shares for retirees for the daily optimization horizon depending on charging power, location and generation source compared to the corresponding AFAP values.

Retired Daily	**Home**	**Home + Work**	**Home + Work + Leisure**	**Home**	**Home + Work**	**Home + Work + Leisure**
10 kWh		**AFAP**			**Smart**	
3.6 kW						
Wind	52.86%	53.22%	50.55%	64.37%	64.37%	64.37%
Wind + PV	55.75%	56.29%	64.22%	77.61%	77.61%	77.62%
PV	38.88%	39.10%	52.29%	64.88%	71.80%	72.63%
7.2 kW						
Wind	50.22%	50.66%	49.09%	64.37%	64.37%	64.37%
Wind + PV	55.04%	55.64%	64.12%	77.62%	77.62%	77.62%
PV	40.78%	41.21%	54.02%	66.24%	66.24%	66.50%
11 kW						
Wind	49.27%	49.71%	48.52%	64.37%	64.37%	64.37%
Wind + PV	54.88%	55.47%	63.79%	77.62%	77.62%	77.62%
PV	41.59%	42.01%	54.37%	66.39%	66.39%	66.51%

faster and thus potentially during times with less renewable generation. The impact of additional charging locations is higher as it contributes to a notable increase of utilized renewable energy. This effect is strongest for employees that employ PV for their AFAP charging, with an increase of 21.9%, corresponding to a doubling of the home only value (cf. Table 5.6). In the case of optimal daily charging the charging power slightly increases the utilized share of energy. In the case of employees the tendency is not monotonous, as the optimal share of wind energy in the home charging location is higher for 7.2 kW (63.02%) as in the 11 kW case (62.78%). For retirees the similar monotonous tendency can be observed, that higher charging powers slightly increase the share of utilized renewable energy. A more distinctive impact is coming from the generation portfolios that encompass PV. For these, one can observe that additional charging infrastructure can increase the share of renewable energy only for employees, whereas retirees remain on similar levels even when additional charging locations and higher charging powers are available. The sensitivity analysis for the daily optimization horizon thus quantifies the importance of additional charging infrastructure at external locations in particular for employees with PV in their generation portfolio.

Discussion and Computational Considerations

The various weekly and daily optimization scenarios presented in this section were mostly performed under similar assumptions for the starting and end SOC. For employees the start and end SOC values in the weekly analysis was chosen to be 20 kWh, representing an SOC of 63.59%. This assumption and the similarity of the starting and end SOC values enabled a continuous analysis over the time frame of 51 weeks based on generation data from 2009. The value of 20 kWh was chosen in order to allow vehicles to charge already at the beginning of the week if e.g., wind power would be available. Higher starting and end SOC values in turn reduce this flexibility and lead to lower values than the ones presented above. For employees the start and end SOC value was consistently 10 kWh, corresponding to only 31.74% SOC. This rather low value was chosen in order to allow for a full comparability of weekly and daily optimization results. For employees in turn the start and end SOC value needed to be adapted to 15 kWh (47.61%) in order to still enable a consistent and comparable number of feasible solutions in the daily optimization. This shows that the potential to integrate renewable energy highly depends on the assumptions about the minimum SOC level requirements that EV users demand. Higher SOC levels are likely

Table 5.8: Overview of feasible solutions in the daily optimization case for employees.

Employees Daily Opt.	**Home**	**Home + Work**	**Home + Work + Leisure**
15 kWh		**Infeasible Days**	
3.6 kW	102	51	0
7.2 kW	51	51	0
11 kW	0	0	0

not to enable feasible solutions for a centralized optimization approach like the one employed in this section. Also lower charging powers lead to additional infeasible days in the daily optimization scenario.

Table 5.8 summarizes the number of feasible and infeasible days for the daily optimization scenario for employees. The main differences with respect to the number of feasible days stems from the available charging power and the number of charging locations. Generation sources in turn do not have an effect and are therefore also not considered in this table. It can clearly be seen that additional charging locations enable more feasible daily solutions as they increase the availability of the EV to fulfill the given constraints. Higher charging powers have a similar effect as they enable the EV to recharge faster in the time slots that are available, even only in the reference scenario with 11 kW charging power.

A closer look on the computation times and the nature of the infeasible days for employees in the home charging case with wind and PV at 3.6 kW shows, that the days that do not allow for a feasible solution are the same in every week. In particular Wednesdays and Thursdays are not feasible for the given driving profiles (cf. Figure 5.10), conventional generation and battery energy level specifications. These days are characterized by additional trips on the early afternoon by a part of the vehicles which leads to additional demand that can not be covered in the specified scenario. In this context it can also be observed that an optimal solution is dependent on the requirements of the entire EV fleet and thus cannot account for individual requirements. A possibility to obtain more feasible solutions in the daily optimization scenario would be to characterize the EVs by their daily driving energy requirements and thus vary the start and end SOC condition in dependence of the respective range requirements.

What can also be observed in Figure 5.10 is that for higher charging powers only Thursday remains infeasible in the daily optimization under the specified conditions. In the particular example the computation times per day also increase but remain on a negligible scale even for intraday operations. There are

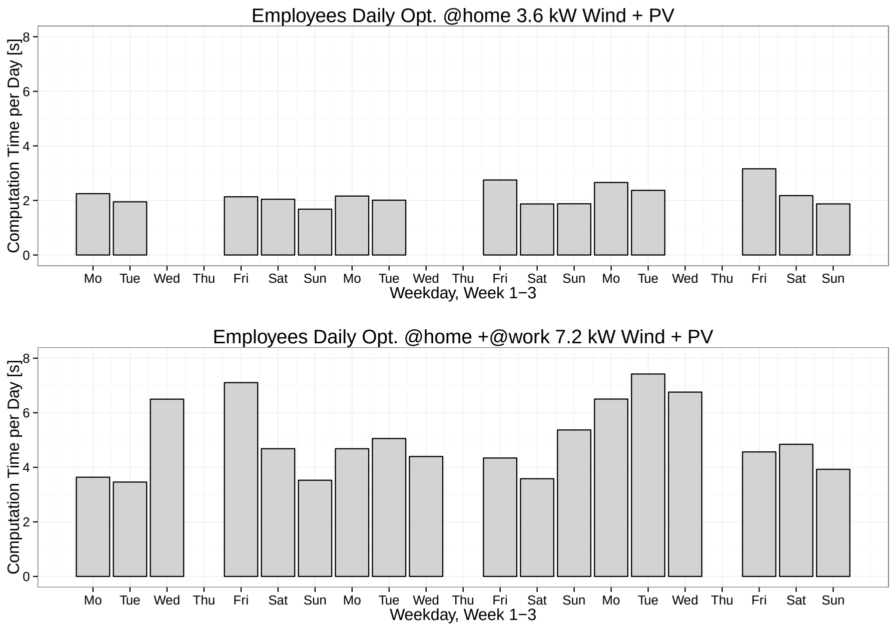


Figure 5.10: Computation times and feasibility per day for the employee home and home + work scenarios at 3.6 and 7.2 kW.

scenarios though, that did not behave in this way with respect to computation times (cf. more details in Appendix G). In particular scenarios with retirees at 3.6 kW charging power and PV as the only generation source lead to considerable computation times in the weekly as well as in the daily optimization. As noted in Table 5.5 some of the reported values represent the 5% optimality gap solutions, as the optimal solutions ran out of memory of the available computational resources. This again gives practical evidence that centralized optimal solutions can be hard to compute, even when resources are available, thus opening up the case for decentralized coordination mechanisms.

5.2.4 Conclusion

The model presented in the previous sections evaluates the general ability of EVs to utilize fluctuating renewable energy sources for charging, while considering the mobility requirements of full time employees and retirees. The model quantifies the ability of the EVs to adapt their charging demand in such a way that the conventional generation that needs to be employed by the EV fleet aggregator is minimized in the analysis time frame of one year. The share of renewable energy from wind power that can be utilized on average by employees in the optimal base case is 84% as compared to 41.24% in the uncoordinated AFAP charging approach. This is about twice of the initial amount and shows the potential of EV demand flexibility. For retirees the wind power utilization over the analysis time frame is increased from 52.86% in the AFAP case to 79.70% in the optimal smart charging scenario. Retirees already have a higher base level of utilized renewable energy which is mainly due to their higher availability for charging at the home location in the base case.

When a mix of wind power and PV, or only PV is employed as a source for EV charging, it can be observed that for both groups the equally mixed generation portfolio of wind and PV is performing best with respect to the utilized share of renewable energy. In particular, the highest values of the entire analysis are achieved by this generation mix. For employees 85.38% (with a max. of 86.96%) of demand, and for retirees 83.42% of demand can be covered by this renewable source-mix. AFAP also exhibits the highest utilization shares in this case but the absolute improvement through the optimization is similar as in the wind generation scenario. A PV only portfolio in turn has very different adoption potentials. In particular employees only charging at home, can not take advantage of this generation source in the AFAP case. This is incorporated in a comparably low utilization share of 22.60%. For optimal smart charging in turn this value can be increased to 65.98% for the home location.

Retirees can also increase their PV adoption share from 41.59% (AFAP) to 68.12% in the optimal case. The significant difference in the AFAP case between retirees and employees results from the fact that retirees are more likely to be available at the home charging location than employees. The AFAP share subsequently increases when additional charging locations are added. The effects of additional charging locations are strongest in the PV case, wind and the mixed portfolio do not profit from additional infrastructure as much as PV does, both in the AFAP and optimal case. For smart charging it can be observed that adding charging opportunities at the leisure location does not significantly increase the RES adoption.

Higher charging powers do not have a high impact on the adoption share of renewable energy in the optimal case, the only significant increase can be observed for PV as a source and the switch from 3.6 kW to 7.2 kW. A further increase to 11 kW does not yield any substantial improvement. This is the case for both groups and shows that if information about trip behavior is available, no high charging powers are required. For AFAP charging, lower charging powers lead to higher adoption rates, as the vehicle can, by chance, charge for a longer time which can also incorporate times with higher renewable generation.

A shorter optimization horizon, in this case a period of one day, can approximate decisions with a high degree of information about planned trips and fluctuating generation. The adoption share of renewable energy drops from 84% to 62.54% for employees and 79.70% to 64.37% for retirees in the optimal wind power case. The load pattern analysis shows that charging occurs more often which leaves a considerable part of the inter day flexibility potential of the vehicles untouched. The minimum battery energy level and the minimum run constraints of the conventional source thus lead to less renewable energy that can be utilized in the analyzed daily optimization setting.

Wind power is dominating the other portfolios in the daily setting for employees, if no additional charging locations are considered. Additional charging opportunities in turn allow for a higher availability of the EVs for charging with renewable sources and thus increase the adopted RES in most scenarios. As observed before, PV profits most from additional charging locations for employees. For retirees the optimal adoption share at the home location is already quite high (66.39%) as compared to employees (40.11%). Higher charging powers only slightly increase the adoption share and only have a notable effect for employees that are constrained in their charging locations.

Overall the presented results show that EVs have a considerable flexibility potential that contributes to a better utilization of fluctuating renewable resources and thus help to balance variations in the power grid. The particular effect on local grid segments and the overall system must be assessed in a scenario which considers the conventional load and its interactions with the EVs. This section provides a sound assessment of the flexibility potential of EVs in a deterministic upper benchmark case, while also investigating the effect of a shorter optimization horizon. The presented central coordination approach is effective but also depends on the scale and formulation of the optimization problem w.r.t. the computation times. If in addition EV-owners are not willing to participate in a direct load control program, individual incentives for shifting of charging demand to times of higher RES availability are needed. A price based charging coordination approach for individual RES adoption is therefore presented and discussed in the next section.

5.3 Renewable Energy Integration: Uniform Pricing Model

Following the approach from Chapter 4 this section presents a price based charging coordination approach which builds on individual price incentives to achieve load shifting of EVs. In this particular case the objective of the individual vehicle is to minimize its individual costs under consideration of a hourly changing variable pricing scheme. Following the supply side perspective in this chapter the interests of the EV aggregator are considered (cf. Section 3.2). In particular the aggregator has the objective to minimize the variable costs for the provision of electricity for the EVs having a contract with him. In order to achieve this, he communicates hourly variable prices reflecting the availability of fluctuating renewable supply. Under the assumption that individually rational EV-owners will respond to his price incentives this section is addressing the following research questions:

RQ 4 - Price Based Renewable Energy Utilization: *Which percentage of renewable energy can be utilized by a fleet of EVs if charging is coordinated via a price signal mapping the scarcity of these intermittent sources?*

RQ 4.1 - Sensitivities: *What is the impact of differing maximum charging powers, generation portfolios and EV driving patterns on the ability to use renewable energy for charging?*

RQ 4.2 - Individual Costs: *Which individual costs do EV-owners incur on average, given a full cost assessment of their renewable energy usage?*

The questions are addressed by extending the individual simulation model from Chapter 4 by a component that represents the aggregator and his pricing decisions as well as a portfolio of intermittent renewable energy generators characterized by empirical wind and solar generation data from Germany of 2009. The generation data corresponds to the data presented in the previous section of the benchmark problem formulation and thus enables a basic comparison of the result characteristics. Related work with regard to charging coordination with the goal to integrate fluctuating renewable energy sources has been discussed above, in particular in Section 2.7 and Section 5.2. This chapter provides insight about a decentralized, hierarchical charging approach that considers economic constraints but seeks to increase the direct utilization of fluctuating renewable energy sources.

The findings of this section are mainly based on results from Richtstein & Schuller (2012) which were presented at the 2012 IAEE European Energy Conference in Venice, Italy. The following sections will describe the model adaptations for the aggregator scenario (Section 5.3.1), the input data and assumptions about the scenario (Section 5.3.2), the results obtained with regard to the research questions (Sections 5.3.3 -5.3.7) and draw conclusions for the price based charging coordination approach (Section 5.3.8).

5.3.1 Model Structure

The model structure is determined by the two main entities that are represented (cf. Figure 5.11): An aggregator who publishes electricity rates (p_t) for each time slot (t) for the analysis period (time frame T, here one week), and several EVs which then individually decide when to charge. The EVs follow the individual cost minimization approach presented in chapter 4.2. The simulation is performed in a similar way as for the benchmark model: a weekly optimization is repeated for 52 consecutive weeks, thus mapping an entire year of renewable energy oriented EV charging with data from 2009. As before, the model specifies similar starting and ending conditions for the relevant variables such as SOC, thus enabling this continuous analysis.

The Aggregator

The decision of the aggregator on how to set the value of the electricity rate p_t is performed by a calibrated heuristic following the goal to match the demand of the EVs with the intermittent renewable generation as closely as possible, given individually optimizing price responsive EVs.

Two main variables are used by the aggregator to determine the electricity rate p_t: First, the amount of the current renewable generation in relation to the renewable peak generation in the analysis time frame of one week (g_t/g_{max}) is employed as an indicator for relative renewable generation scarcity, following the rationale applied in Chapter 4 to shift demand to the time slots with the highest renewable generation share in relation to total load. Second, the general availability of the EVs for charging a_t, i.e. the percentage of vehicles that is connected in a given time slot t, is considered. This variable serves as an indicator for potential demand, since it determines the upper bound of potential

Table 5.9: Uniform Pricing Model Parameters

Parameter Description	**Symbol**	**Domain**
Operational battery capacity	C	(kWh)
Min. number of time steps to fully charge	ν^c	(#)
Charging efficiency	η^c	(%)
Storage cost	ψ	(EUR/kWh)
Price per energy unit in time step t	p_t	(EUR/kWh)
Charge parameter for time step t	φ_t	(%)
Energy level of the battery at time t	L_t	(kWh)
Energy consumption in time step t [a]	d_t	(kWh)
Location of the BEV	z_t	(0: not at home 1: at home)
Total generation	g_t	(kWh)
Intermittent generation	$g_{t,I}$	(kWh)
Maximum $g_{t,I}, t \epsilon T$	$g_{max,I}$	(kWh)
Renewable generation and availability costs	$p_{t,R}$	(ct/kWh)
Conventional generation	$g_{t,C}$	(kWh)
Conventional generation costs	$p_{t,C}$	(ct/kWh)
Total load in time slot t	l_t	(kWh)

[a] d_t = kilometers driven in time step t (km) $\cdot$ power consumption per km (kWh/km)

demand in case that a considerable number of EV-owners decide to charge due to relatively low prices. This parameter was introduced as a measure to account for simultaneity effects of EV demand. The impact on the distribution of EV demand is analyzed within the context of the results obtained.

The overall simulation process and structure are depicted in Figure 5.11. The empirical driving profiles serve for the calculation of the EV charging availability at the home location and also as main constraints for the formulation of the individual cost minimization problem of the respective EVs. The aggregator in turn generates a price based on the scarcity of renewable energy and the overall availability at the home charging location. This price in turn serves as the main input for the individual EVs to make cost minimal charging decisions. All non-renewable demand resulting from these individual decisions it covered by the conventional generation.

While relative generation abundance (i.e. a high $g_{t,I}/g_{max\forall t \in T,I}$) will result in a lower price, times of high potential demand (i.e. a high a_t) will in turn balance this effect and lead to higher total electricity prices. This relation which was described above is formalized in the following expression:

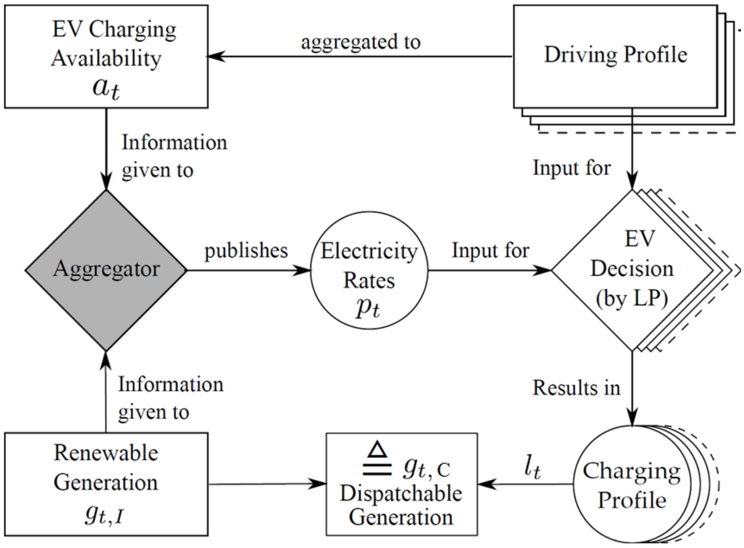


Figure 5.11: Simulation model structure and general interactions between the roles.

$$p_t = \begin{cases} p_{t,C} & \frac{g_{t,I}}{g_{max,I}} \leq 0.05 \\ \underbrace{(1 - \frac{g_{t,I}}{g_{max,I}}) + w_a \cdot a_t}_{p_{t,R}} & \text{else} \end{cases} \quad , \forall t \in T \tag{5.12}$$

For periods in which little or no renewable generation is available (i.e., if renewable generation drops below 5 % of its weekly maximum) the price is set to the limit $p_{t,C}$, to further discourage charging. The level of 5 % is chosen in order to maximize the share of used renewable generation before relying on conventional generation and thus follows the same economic rationale as in Section 5.2, to minimize variable generation costs. Please observe that no further ramping or minimum run time constraints are imposed on the conventional generation in this particular case. This also supports a different economic evaluation approach in which the individual charging costs are assessed by the hourly prices from the European Energy Exchange (cf. Section 5.3.7).

The Individual Vehicles

The charging behavior of the vehicles is modeled using a linear optimization program that was introduced earlier in Section 4.2 thus incorporating the "Smart Charging Strategy" based on variable price incentives for every EV. The model constraints are consistently formulated as above: The state of charge of the battery needs to be in between 0 and the operational battery capacity at all times (Eq. 5.14). In addition the energy consumed corresponds to the energy that needs to be recharged during each optimization period of one week (Eq. 5.16. Further it is assumed that the battery of each EV is fully charged at the beginning of every week, and consequently needs to be fully charged at the end of the week in order to allow for a continuous evaluation over the course of 52 weeks of the year 2009. This potentially slightly reduces the flexibility of the vehicles to react to high renewable energy generation availability but provides a more conservative insight with respect to the mobility requirements of the EV-owners.

$$\min_{\varphi_t} \rightarrow Cost = \sum_{t=1}^{T} \underbrace{p_t \cdot \varphi_t}_{Electricity\ Costs} \tag{5.13}$$

$$C \geq \underbrace{L_{t-1} + \frac{C}{\nu^c} \cdot \varphi_t - d_t}_{SOC_t} \geq 0,\ \forall t \in [2, T] \tag{5.14}$$

$$C \geq \underbrace{L_1 + \frac{C}{\nu^c} \cdot \varphi_1 - d_1}_{SOC_1} \geq 0,\ t = 1 \tag{5.15}$$

$$\sum_{t=1}^{T} \frac{C}{\nu^c} \cdot \varphi_t = \sum_{t=1}^{T} d_t,\ \forall t \in [1, T] \tag{5.16}$$

The objective function of each vehicle is to minimize the incurred charging costs (Eq.5.13). These are determined by the amount of energy charged times the electricity rate p_t. Additional degradation costs are not considered in this section, since the amount of energy charged by the vehicles is similar both for AFAP and smart charging. For V2G operation strategies storage costs need to be considered (cf. Section 4.3), for purely operational analyses this is not necessary if only the electricity costs are considered. As the focus of this section is on the price based charging coordination for renewable energy utilization the more detailed implication of storage costs was already performed in section 4.3 for the individual assessment.

$$\varphi_t = \begin{cases} 1 & : \text{if } SOC_t + \frac{C}{\nu^c} \leq C \text{ and } z_t = 1 \\ \frac{C - SOC_t}{\frac{C}{\nu^c}} & : \text{if } SOC_t + \frac{C}{\nu^c} > C \text{ and } z_t = 1 \\ 0 & : \text{otherwise} \end{cases} \tag{5.17}$$

As a reference case uncoordinated AFAP charging is again included in the analysis. Here it is assumed that vehicle owners charge as soon and as fast as it is possible after they arrive at the charging location, which is realistic, since this strategy minimizes the risk to have an empty or too little charged battery when the vehicle is needed. In the model notation this behavior translates to equation 5.17.

5.3.2 Input Data and Assumptions

Similar to the analyses presented before this section describes the empirical inputs employed for the simulation based analysis. As most input parameters were already described in more detail in the previous sections only the model inputs deviating from the previous specifications are described in more detail.

Mobility Profiles

The driving profiles are consistently from the German mobility panel (BMVBS, 2008), the study that continuously collected data about the day-to-day mobility behavior of German citizens from 1994 up until 2007. The driving profiles include all car trips within a specified week of the year that have been made by a certain person. For each trip, the following information is provided: start, end, duration, distance, average speed, and purpose of the trip. In this section the 1000 moste recent profiles of four demographic groups were chose for the analysis: employees, retired, part-time employed and unemployed. This expands the previous investigations. From the respective 1000 profiles the subset that could be fulfilled at the minimum charging power of 1 kW were subsequently employed for this analysis. The customer portfolio of the aggregator is further assumed to consist to equal parts of the four sociodemographic groups. In order to reduce the computation times for the different parameter permutations each simulation scenario is performed with 25 randomly chosen profiles for each group. In addition a scaling factor is introduced in order to map the capacities and demand requirements of a fleet of 1000 vehicles. For one scenario with a predefined set of parameter combinations the profiles are kept constant in order

Table 5.10: Electric Vehicle Specification, according to Nissan (2013).

Specification	Nissan Leaf
Battery Capacity [kWh]	24
Operational battery capacity (C) [kWh]	21.6
Maximum Speed [km/h]	145
Maximum Range[km]	160
Battery Type	Li-Ion
Charging Efficiency (η_c)	93

to allow for comparable results.

Electric Vehicle Specifications

To ensure realistic assumptions about the modeled EVs, specifications from one of the first mass-produced EVs are employed: the Nissan Leaf. However, some simplifications needed to be made to accommodate for the linear limitations of the employed individual EV model: Charging is assumed to be linear in time ($t_{FC,x\text{kW}} = \frac{C_u}{\eta_c * x\text{kW}}$), and equally discharging is assumed to occur linear in dependence on the driven kilometers. The Nissan Leaf has a slightly smaller battery than the vehicles considered in the analyses before, nevertheless the number of feasible driving profiles is in a comparable range to the other sections.

Intermittent Generation

Wind and solar generation data are similar to Section 5.2 and obtained from the German transmission system operator 50Hertz. The data is adjusted to account for capacity built up during the year 2009. Please observe Table 5.1 for the summary statistics and characteristics of the employed data. The generation data is available in 15 minute time steps, and similar to the benchmark case, scaled down for the simulation such that the yearly production exactly accounts for the yearly consumption of the EVs. As a result there are weeks with over and under supply of intermittent renewable energy from wind power and PV. In the investigated base case scenario the resulting wind power capacity is slightly below 700 kW and for the PV scenario 1.1 MW of capacity are required in order to deliver the necessary electricity. This dimensioning approach for the generation of the aggregator is further evaluated in section 5.3.8.

Assumptions

The adapted model depends on several assumptions which result from the deterministic nature of the linear program. Many of them are similar to the assumptions formulated in Section 4.2, but also summarize the distinct features of this section:

- The time frame of one optimization is one week.
- The granularity of optimization is 15 minutes.
- The driving patterns are known ex-ante to the drivers for the week ahead.
- The electricity rates are published ahead of the time frame and are known to the drivers.
- The driving profiles of the vehicle owners must be fulfilled.
- At the start and end of the time frame the battery needs to be fully charged.
- EVs can only be charged at home.
- When EVs are at home, there are no restrictions on charging, except EV specifications (including maximum charging power and battery capacity).
- Driving behavior does not change as compared to ICEVs.
- The aggregated charging availability $\vec{a}$ is known ex-ante to the broker.
- The production portfolio consists of uncontrollable renewable intermittent energy sources and conventional generation which is immediately available if necessary (i.e. there are no ramping constraints).
- Intermittent generation data $\vec{g}_I$ for each time frame is known ex-ante to the aggregator such that he can generate a variable price set for the optimization period.

5.3.3 Base Case Evaluation

In this section the scenario setup and the results with respect to renewable energy utilization under consideration of variation of charging power, generation portfolio and driver type are going to be presented. The economic impacts are discussed in Section 5.3.7.

The base case serves as a reference for the different alterations of parameters and is defined in such a way that it represents a fleet of EVs which is characterized by its driving profiles, the allowed (constant) charging power and the utilized renewable energy sources. This base case scenario is defined as follows: the four different driver groups are evenly distributed, and each group accounts for 25% of the 100 vehicles analyzed. The vehicles are restricted to a German standard one-phase AC outlet of 3.6 kW for charging power and solely attempt to use wind power for their charging. The Fleet consists only of one type of electric vehicle, the Nissan Leaf (cf. Table 5.10).

All further scenarios are evaluated with respect to their capability of direct renewable energy utilization. This is quantified by the average percentage of renewable energy utilized by the EVs in charging over the investigation period of one year (further denoted as $R_{\%}$), calculated as the average relative value for all time slots.

$$R_{\%} = \frac{\sum_{t \epsilon T}(l_t) - \sum_{t \epsilon T}(g_{t,C})}{\sum_{t \epsilon T}(l_t)} \tag{5.18}$$

As presented in section 5.3.1 the variable pricing scheme communicated to the EVs has two distinct parts. The first term (cf. Eq. 5.12) inversely maps the availability of renewable energy in relation to the generation maximum of the week under investigation. The second part introduces a weighting factor accounting for the general charging availability and thus the increased potential demand. This in turn is increasing the variable price in the same time interval. As in the next paragraphs only the combined effect of the aggregated price signal is evaluated, first the effect due to the two price components in the base case is evaluated.

The simulation results show for the base case in which only the renewable generation signal without the availability component is applied (Markel et al., 2009), i.e. the lowest price is set for period with the highest production of renewable energy), that EV-demand is shifted extensively to times of higher renewable energy availability. In this scenario the EV demand is considerably higher than the available energy, as all vehicles concentrate their charging activities during the favorable time slots, thus creating new coordinated peaks (cf. Figure 5.12).

When the charging availability of the EVs is accounted for, the EV-demand becomes more distributed and has smaller peaks which still exceed the renewable generation (cf. renewable signal and base case in Figure 5.12) This charging behavior shows that charging coordination of a substantial amount of vehicles that reacts to the same distinct price information but in terms of capacity could be served by a specified generator, can cause new undesired peaks. This shows that a more individual feedback mechanism incorporating the remaining unused capacity per time slot of renewable energy in the local distribution grid setting should be further investigated.

The coordinated peak effect is exemplified in Figure 5.12 for one week of the year 2009, but can be confirmed when looking at the rest of the analyzed data

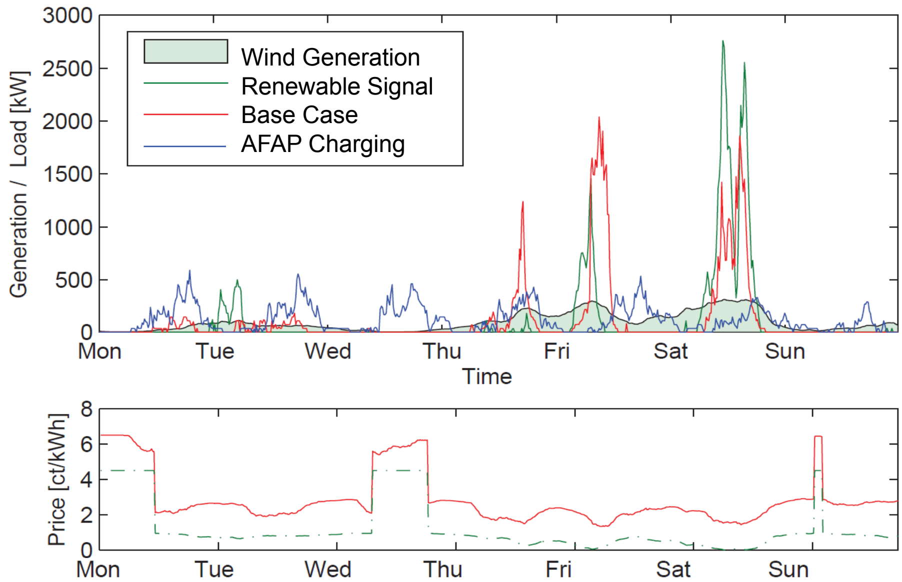


Figure 5.12: Wind generation and EV-consumption for one week (week 51) matching for all driver groups as compared to the applied price signal at 3.6 kW

set (cf. Figure 5.13). There it can be seen that the renewable signal load is mostly 30-50% higher, or in extreme cases even double as high as the base case load (cf. week 16). The average renewable energy utilization ratios for the different charging strategies show that by chance the uncoordinated approach has a higher ratio of 47.92% in contrast to the renewable generation signal strategy which only accounts for 31.45% on average due to the occurred overcoordination of demand to renewable generation peaks. The base case performs slightly better with a share of 40.32% of renewable energy utilized.

It can be observed that for the specified base case, coordination works "too well" as all EVs use the same distinct information about wind power availability, thus exceeding the available amount of renewable energy, whereas in other time slots renewable energy is not used to its full potential. Following this observation different analyses investigating the impact of alteration of charging powers, driver types, charging availability and generation portfolios on the performance with respect to renewable energy integration and peaking behavior are described in the next section.

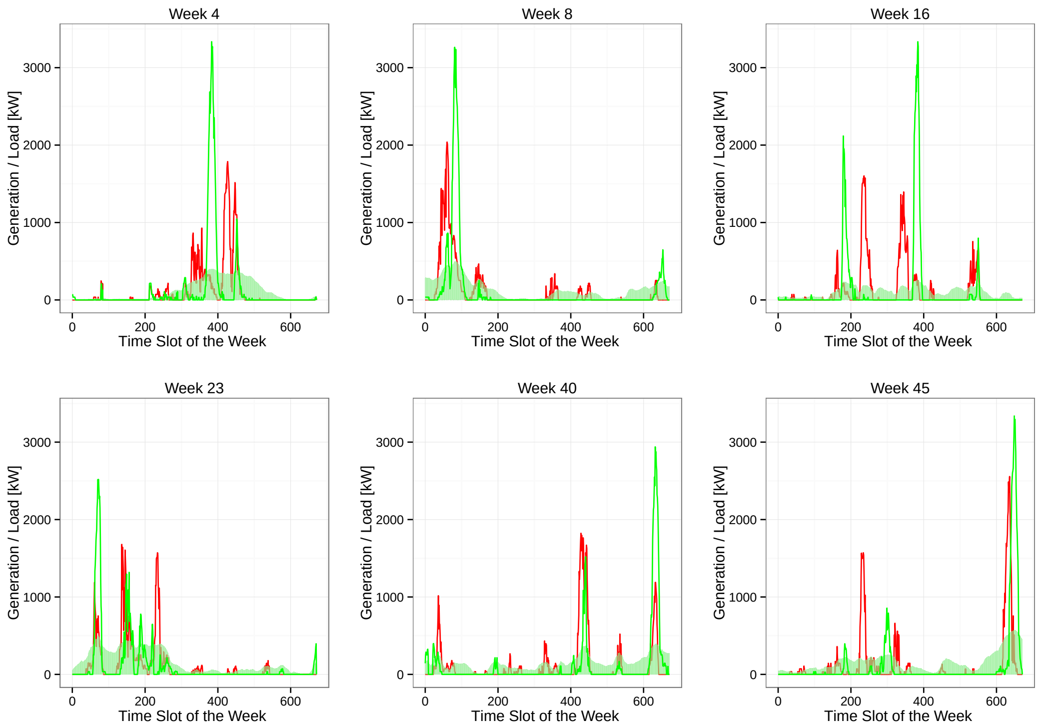


Figure 5.13: Comparison of the base case (red) and renewable signal loads (green) for different weeks of the year 2009.

5.3.4 Impacts of Charging Power

The impact of charging power on EV demand and the resulting utilization of wind power is substantial. Higher charging powers allow for shorter charging times, thus increasing the available potential driving range. On the other hand, lower charging powers enable a smother load pattern of EV demand, implying less stress on the grid and its local operating components. The investigated charging power rates in this section are therefore 1, 2, 3.6 and 11.1 kW, covering the most common power ratings which can be applied at any home charging station or even simple one phase standard sockets. Higher charging rates are not considered, as they are not likely to available in a private setting, but only through public or commercial infrastructure.

As experienced in the base case, secure and common knowledge about renewable energy availability will cause additional demand concentration around the projected renewable generation peaks. In this context the charging rate can highly accentuate this grouping behavior, or if introduced as a constraint can

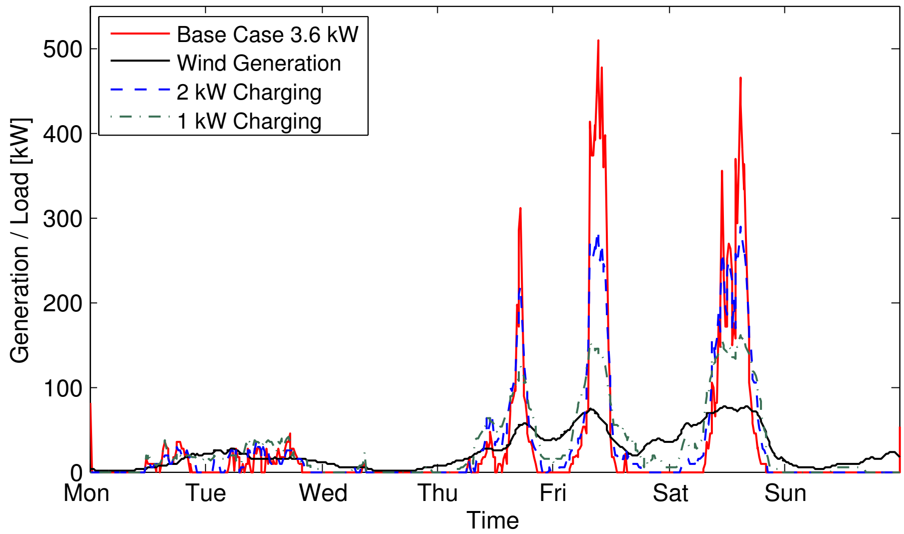


Figure 5.14: Example of the impact of different charging power rates on wind power consumption for week 51 matching for all driver groups.

ameliorate the effects of high coinciding demand patterns. This effect can be observed in Figure 5.14 where the base case (charging at 3.6 kW) load is compared to two settings with lower power ratings being 1 kW and 2 kW and the respective generation for this particular week. It can clearly be seen, that higher charging powers lead to over-accentuated peaks while utilizing less renewable energy. The slow charging approach of 1 kW is best in this case to reduce the concentration of EV demand while using a higher share of the available renewable sources. However this low charging rate represents a rationing of available capacity.

In the 11 kW case only 25.96% of EV demand are satisfied on average over the year from wind energy. For decreasing charging powers in turn it can be observed that the utilization rate $R_{\%}$ is increased from 40.32% in the base case to 50.14% in the 2 kW and up to 63.95% in the 1 kW slow charging case. Lower charging powers contribute to a higher average utilization rate of renewable energy, in particular because EV demand is better distributed around times of higher wind power availability. Charging at lower rates is also more beneficial for local substations and distribution equipment and prevents the need for grid infrastructure expansion.

But these beneficial effects of lower charging powers come with constraints with respect to the flexibility of EV-owners. As denoted in Table 5.11, it can be seen that in the 1 kW case only about 57% of the *employees* in the original 1000

Table 5.11: Effect of charging power variation on average driving range and ratio of satisfied driving profiles per group.

Charging Power	Employees	Part-Time	Retired	Unemployed
1 [kW]	57%	76%	71.7%	76.5%
km/Week	175.61	133.06	101.01	91.26
2 [kW]	66%	80.4%	77.5%	81.4%
km/Week	205.88	140.80	108.22	98.21
3.6 [kW]	70.4%	83.7%	80.6%	83%
km/Week	217.95	148.06	114.21	100.54
11.1 [kW]	72.1%	84.8%	82%	83.8%
km/Week	220.34	150.68	115.77	101.62

profile data set can be charged such that their driving requirements are met. The other groups still have a higher temporal flexibility and all have more than 70 % of viable profiles in this scenario. As charging rates increase, the number of viable profiles and the average weekly distance that can be traveled also increases. In the best case when 11.1 kW can be used for charging this allows for 72.1% of the *employees* to be charged accordingly. Other driver types have a viable amount of profiles of at least 82%.

For this section it can be concluded that charging powers highly affect demand peak patterns and thus the possible driving distances for the four different driver groups. Also lower charging rates can contribute to a higher share of renewable energy utilization in the given scenario while additionally reducing stress on distribution equipment.

5.3.5 Impacts of Generation Portfolio

While wind power is one of the predominant renewable sources it is not the only one with major contributions in the German energy system. Solar photovoltaics (PV) is the second major renewable energy source when considering the installed overall capacity (around 10 GW for 2009 (BNetzA, 2010)). Because of this and the variability that it has in common with wind power it is also employed in the following analysis. The impact of three different generation portfolios is evaluated with respect to the base case setting and variation of charging power. The results show that for PV the average yearly $R_{\%}$ is higher when considering the same scenarios as before. The $R_{\%}$ in the base case is with 55.88% substantially higher than in the wind only case with an $R_{\%}$ of 40.32%. The same results are obtained

Table 5.12: Relationship between generation technology and charging power with respect to $R_{\%}$

Generation	1 [kW]	2 [kW]	3.6 [kW]	11.1 [kW]
$R_{\%Wind}$	63.95%	50.14%	40.32%	25.96%
$R_{\%PV}$	68.6%	64.97%	55.88%	39.12%
$R_{\%Mix}$	75.45%	60.69%	49.86%	34.06%

if lower charging powers are considered. For the case of 1 kW the $R_{\%}$ of PV is still higher with 68.6% as compared to the value of 63.95% of wind power (cf. Table 5.12).

PV is less volatile in its production patterns than wind and times when it is surely not available can be mostly well defined. The generation pattern with a peak at noon maps well onto the resulting load patterns of the EVs given the renewable energy and availability dependent rate. This effect can be observed for example in Figure 5.15 where the load resulting from *employees* and *retired* drivers is mapped with the generation from PV. It can be seen that for these exemplary weeks in August the charging load of *employees* and *retired* can be more than satisfied. The other interesting pattern in this context is that retired drivers are charging predominantly during the week, while employees charge during morning and evening hours and especially on the weekend, when they are likewise available during the daytime. PV generation thus does accentuate the different charging availabilities of the individual groups and contributes to a more distributed load pattern, which on average still utilizes more renewable energy than a wind-only generation portfolio. The mixed generation portfolio has an average $R_{\%}$ of 75.45% over the whole year which is higher than in the PV only case yielding 68.60% in the 1 kW scenario. The overall performance during the course of 2009 of the mixed generation portfolio is depicted in Figure 5.16.

During this period it can be seen that especially in summer when PV production is prevalent, the overall utilization of renewable power through the vehicles can almost always be higher than 90% given the mixed portfolio. In this setting the slightly complementary seasonal generation patterns of PV and wind power are observed. For the impact of different and in particular in this case intermittent generation sources, on the ability to be utilized by the EVs, it can be concluded, that a differentiated generation portfolio in combination with the given EV driver portfolio can better accommodate for a high share of renewable energy. Higher average renewable shares can also be achieved by increasing the

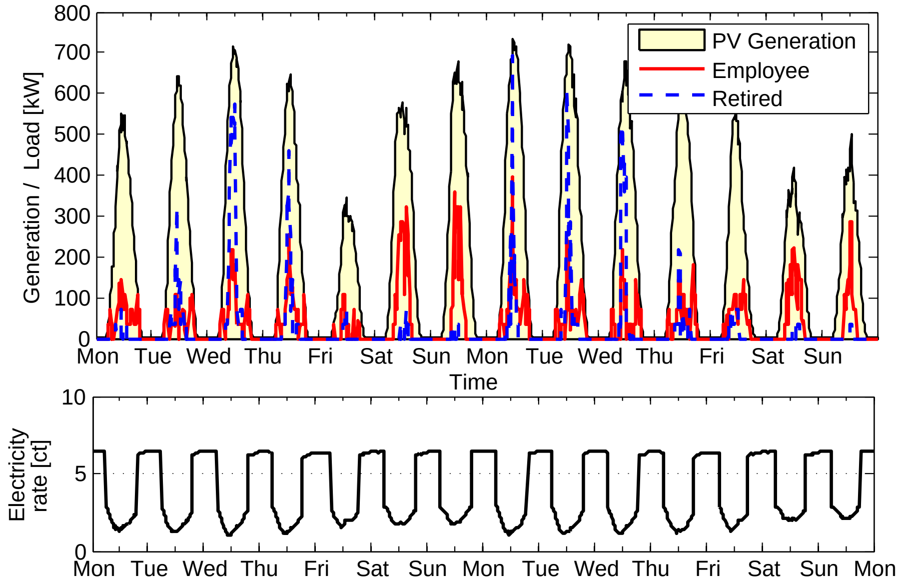


Figure 5.15: Charging from PV in Week 31 and 32 and resulting load patterns for employees and retired drivers

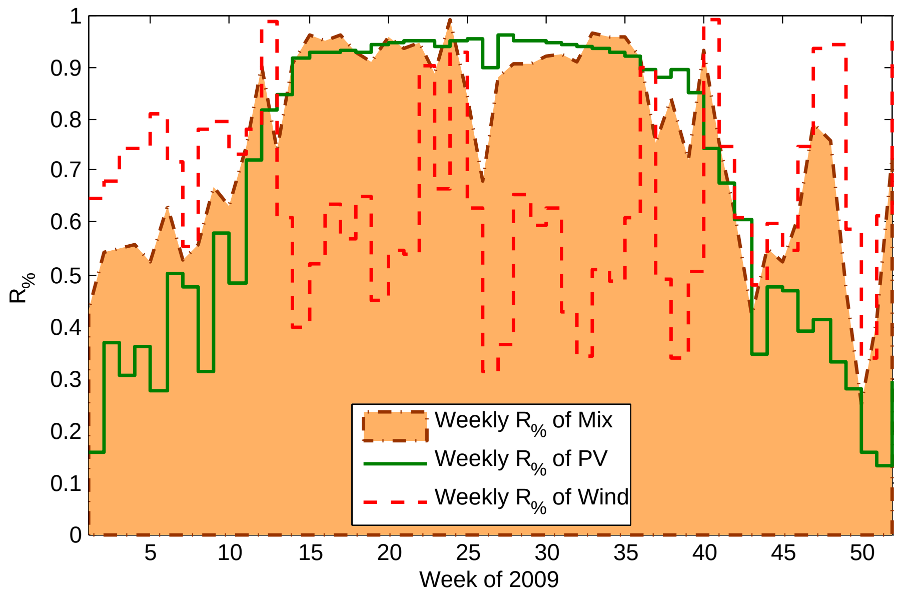


Figure 5.16: Weekly average share of intermittent electricity in charging of the generation portfolios in the 1 kW case

Table 5.13: Renewable energy utilization rate for different driver groups and correlation matrix (r) for similar demand patterns

$R_{\%}$		**Employees**	**Part-Time**	**Retired**	**Unemployed**
48.05%	Employees	1.00	0.68	0.62	0.71
33.05%	Part-Time	0.68	1.00	0.84	0.89
23.81%	Retired	0.62	0.84	1.00	0.92
26.78%	Unemployed	0.71	0.89	0.92	1.00

capacity of the available generation portfolio. But as this will also incur additional cost to a EV charging coordinator or aggregator the approach of parity in demand and generation serves as a conservative baseline.

5.3.6 Impacts of Driver Type and Portfolio

The results of distinct simulation runs with similar prices for all groups show that employees have the highest individual renewable utilization rate with 48.05%. Part-Time employees follow with 33.05%, whereas retired and unemployed drivers only have utilization rates of 23.81% and 26.78% respectively, cf. Table 5.13. Please observe that these values refer to the 3.6 kW base case setting with wind generation.

The correlation analysis (cf. Table 5.13) provides insight with respect to the similarity of the demand patterns of the different driver groups. The analysis shows that employees have a substantially different load and underlying driving pattern which leads to a higher utilization of renewable energy in the base case. *Part-Time employees*, *retired* and *unemployed* on the other hand are more similar to each other in their load patterns. The lower $R_{\%}$ for these groups also results from the utilization of the same price for all groups. Part-Time employees, retired and unemployed drivers have a higher charging availability, which does not vary that much as the one of employees. This in turn leads to the fact that even as they would have a higher flexibility with respect to their charging times, they also choose the time slots in which generation is highest. As all groups have the same price information this leads to the accentuated peaking behavior observed in the previous sections. For the analysis in this section it can be concluded that a differentiation of driver profiles leads to a higher $R_{\%}$, especially if more employees are added in the portfolio. This is due to their higher demand as compared to the other groups, which, due to the restrictions of the battery capacity of the EV, makes them recharge more often. This opens up the opportunity to use several time steps in which renewable energy is available, whereas the other groups concentrate their small demand around singular moments in the optimization period. At the same time another conclusion must be, that a different price for every group taking more advantage of the individual flexibility must be implemented in order to improve the overall utilization of renewable energy for driving.

5.3.7 Cost Evaluation

While the previous sections had the focus on the utilization rate of renewable energy, this section is concerned with an individual cost evaluation of the charging strategies performed by the EVs. The load resulting from optimization of the EVs according to the proposed tariff rate from expression (5.12) can be assessed in economic terms at the actual production costs of the underlying technology for renewable generation. This perspective enables a cost based assessment of the charging decisions, and a comparison with current and planned dynamic end-customer rates for electricity. The underlying assumption in the following evaluation is that the average production costs (including capital costs, according to (Sterner and Specht, 2010; BSW-Solar, 2012)) are fully passed on to the EV-owner according to the (linearly scaled) proposed dynamic rate. This transformation of the tariff raises the absolute levels, so that the mentioned direct production costs are completely covered. The charging decisions are not affected by the linear transformation, as the relative order or rank of the different time slots remains the same and thus the chosen charging times.

At times in which renewable generation is not sufficient, conventional power is acquired at EEX spot-prices for the respective time slots (EEX, 2011). At times when renewable generation exceeds demand, it is sold at the EEX prices, but only when EEX prices are non-negative. In addition to this generation or production part, taxes and fees as of 2009 in Germany are added to reflect the total costs at end-customer level for every kWh. This enables a cost based assessment on an individual basis for EV-owners and a revenue assessment for renewable energy EV aggregators. In addition to the generation and procurement costs, the additional taxes and fees are accounted for. These are in particular the fixed electricity tax, the CHP fee, the concession fee (granting communal distribution grid access), grid fee (transmission and distribution), value added tax and the EEG subsidy fee that is due for the non-renewable supply from the EEX. Thus all costs at the end-consumer level under current German regulation are considered. Form a supply perspective the costs considered allow enable a strategic assessment. In the following paragraphs the base case scenarios with 3.6 kW and the 1 kW are evaluated with respect to their incurred costs.

Table 5.14: Average end consumer cost split for the 3.6 kW case and different generation sources for the cost minimal charging strategy.

[ct/kWh] \Scenario	**Wind**	**PV**	**Mix**	**EEX**	**EEX > 0**
Production costs	8.83	29.53	19.23	-0.13	1.16
Production costs RES 2012	8.83	22.21	15.52		
Electricity tax	2.05	2.05	2.05	2.05	2.05
CHP fee	0.24	0.24	0.24	0.24	0.24
Concession Fee	1.79	1.79	1.79	1.79	1.79
Grid Fee	5.80	5.80	5.80	5.80	5.80
EEG Fee (for EEX supply)	0.78	0.58	0.66	1.31	1.31
VAT (19 %)	3.70	7.60	5.65	2.10	2.35
Total Avg. Costs	23.19	47.59	35.42	13.16	14.69
Total Avg. Costs RES 2012	23.19	40.27	31.71		
CO2 Emissions [g/km]	46.80	41.27	42.45	76.28	76.28

Table 5.15: Average end consumer cost split for the 1 kW case and different generation sources for the cost minimal charging strategy.

[ct/kWh] \Scenario	**Wind**	**PV**	**Mix**	**EEX**	**EEX > 0**
Production costs	8.76	29.47	19.19	1.35	1.87
Production costs RES 2012	8.76	22.15	15.61		
Electricity tax	2.05	2.05	2.05	2.05	2.05
CHP fee	0.24	0.24	0.24	0.24	0.24
Concession Fee	1.79	1.79	1.79	1.79	1.79
Grid Fee	5.80	5.80	5.80	5.80	5.80
EEG Fee (for EEX supply)	0.47	0.41	0.32	1.31	1.31
VAT (19 %)]	3.63	7.55	5.58	2.38	2.48
Total Average Costs	22.74	47.32	34.97	14.92	15.54
Total Average Costs RES 2012	22.74	39.99	31.39		
CO2 Emissions [g/km]	29.57	33.30	25.09	76.28	76.28

The evaluation shows that there are substantial differences in generation procurement cost between the renewable tariffs and an optimal EEX procurement regardless of the charging power (cf. Tables 5.14 and 5.15). This difference is mainly due to the very low - or even negative - procurement costs on the EEX in the optimal strategy, which can be explained by two factors: (1) The regular nightly low of EEX prices coincides with the availability of vehicles for charging. (2) Spot market prices are variable cost based which can even be negative, whereas the proposed renewable tariffs above are full-cost based. In addition the high price spikes that refund the capital cost of generators on the EEX, can

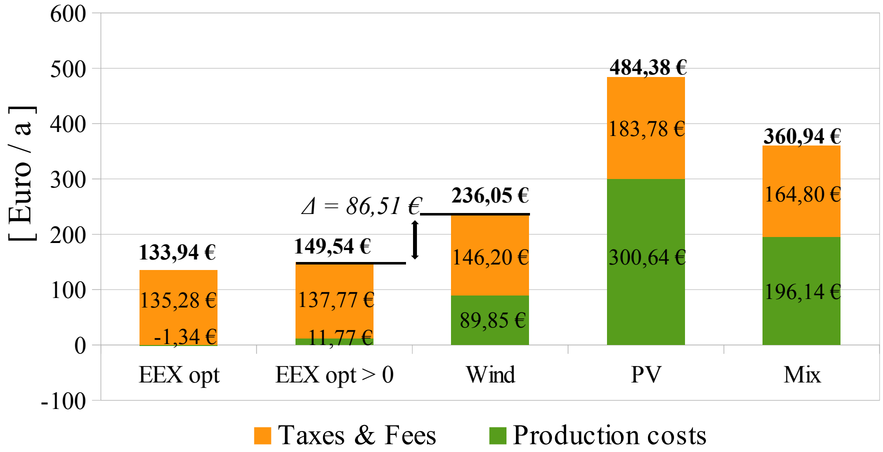


Figure 5.17: Total yearly average end consumer cost for the Wind Power, PV and EEX cases with 1017 kWh/a/EV consumption at 3.6 kW

be avoided by an optimizing EV with perfect weekly foresight. The proposed comparison is therefore accounting for a conservative "worst case" in terms of individual cost for a renewable energy tariff scheme, as opposed to an optimal EEX oriented cost minimizing charging scheme.

However, due to the relative high share of network fees and taxes (BNetzA, 2010) in Germany the difference in end-consumer cost is ameliorated, although still notable. The difference of the base case as compared to an EEX only procurement amounts to 102.12 Euro/year or 86.51 Euro/year (see Figure 5.17), if negative EEX prices are excluded from the evaluation for the average EV-owner (evenly including all four driver groups). If the same calculation is repeated with the decreased generation costs for PV from 2012 (assuming a kWp installed price of 2100 Euro(BSW-Solar, 2012)), the average total costs drop significantly from 484.38 Euro/year to 409.84 Euro/year in the PV case. In this context it should be noted however that the average costs in the case of wind being 23.19 ct/kWh, nearly correspond to the average household costs for electricity in 2009 ranging between 22.75 - 22.82 ct/kWh (BNetzA, 2010; Goerten and Ganea, 2009). In the meantime this value has even increased further and as of 2010 (average of 22.92 - 23.87 ct/kWh) made it economically viable for EV-owners to switch to a predominantly renewable supplier, given the assumptions above hold.

The difference in charging power has only a small effect in overall costs for consumers in the RES cases. This is because of the relatively low prices at which power can be procured from the EEX in the cases where there is a deficit of renewable energy. For EEX procurement the change in procurement costs is more noticeable, and points to the sharp minima of EEX prices, which can be better utilized if a higher charging power is available to the EV-owner. However, due to the higher share of renewable energy used in charging for the 1 kW scenario, the CO_2 emissions are lower than in the 3.6 kW scenario. Only one third of the amount of CO_2 is emitted for the mixed 1 kW scenario as compared to EEX optimization (procurement from the EEX is accounted at the German average of 565 g CO_2/kWh, wind power at 24 g CO_2/kWh and PV at 101 g CO_2/kWh (UBA, 2011)).

With regard to the economic evaluation of the proposed renewable based charging scheme, it can be concluded that even in a conservative cost based approach, wind power based charging which includes capital costs for the generation company, is only slightly more expensive than the fixed German average end-customer rate per kWh of 2009. On the other hand it can be observed that the significant amount of taxes and fees leaves room for improvement, even if the support from the EEG is no longer in place.

5.3.8 Conclusion

The scenario investigated in this section is covering two important aspects of electric mobility. The first is the ability of a price based charging coordination approach to increase the direct utilization of renewable energy given a specified generation capacity of fluctuating sources. The second is the economic evaluation of the resulting charging behavior for different generation technologies and a procurement only strategy. The economic analysis considers current regulation at the end consumer level and provides insight about the economic competitiveness of fluctuating renewable generation sources based on a total cost assessment for the supply side.

Using a uniform price signal in order to coordinate the charging demand of EVs which minimize their incurred costs in a deterministic setting can, under certain conditions, lead to additional demand peaks. These new coordinated peaks can be addressed by including the charging availability in the rate design or by lowering the available charging power for the EVs. These two measures improve the renewable energy utilization rate from 40.32% in the base case (only wind power) to 63.95% in the 1 kW case and even further if a mixed generation portfolio of wind and PV is evaluated, yielding an $R_{\%}$ of 75.45% over the whole year. Still, in these settings the flexibility of the driver groups of *Part-Time employees*, *retired* and *unemployed* is not exploited to its potential, as they also tend to use the same time slots as employees for charging which are more constrained in their charging availability at the home location. Possible approaches for a better demand distribution in this case would be individually differentiated pricing for every group or an iterative process including information feedback about the remaining renewable energy capacity in the price (i.e. a posted price offer process), thus balancing the additional demand for each time period with the available generation capacity.

The utilization of renewable energy in the charging demand is highly influenced by the employed generation technology. In this case PV provided a higher $R_{\%}$ of 55.88% than the 40.32 % of the wind power base case. In this respect it can be seen that the volatility of wind power can not be met by price dependent EV demand as well as the more predictable patterns of PV production. In the case of wind power this calls for a more flexible demand distribution which can be achieved by the mechanisms mentioned above. For PV the investigated scenarios yield higher utilization rates but still lack a sufficient energy provision in the winter time. Therefore a mix of both generation technologies accentuating their complementary generation patterns yields the best $R_{\%}$ with 75.45%.

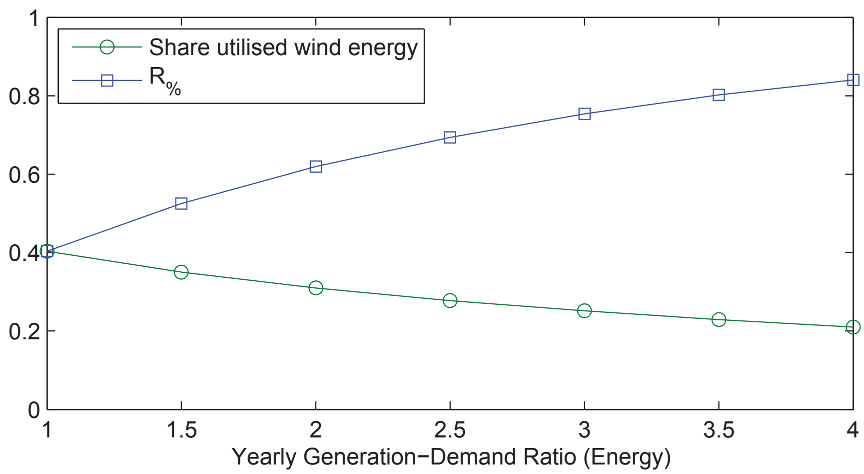


Figure 5.18: Relation between generation and EV demand compared to demand covered by renewable energy.

Further increase of the generation capacity can cover better for demand peaks but also incurs the problem of oversupply for a considerable part of the year. As depicted in Figure 5.18 one can see that in the base case the $R_{\%}$ is increased up to 80% if generation capacity is quadrupled, but at the same time the relative utilization of wind energy is lowered to around 20%. This oversupply can only be ameliorated by additional non-EV-load that is served by the aggregator or by sell-off at the energy exchange.

With regard to the individual economic impact it can be seen that in a total average cost evaluation which is accounting for the capital costs of renewable energy production of the aggregator, the usage of wind power is only slightly more expensive (23.19 ct/kWh) than in a case with normal average power prices for 2009 being 22.82 ct/kWh. For the case of optimal EEX-price based procurement at hourly spot rates it can be seen that the average costs per kWh range between 13.16 and 15.54 ct/kWh. The inclusion of average capital costs in the economic evaluation shows, that even without direct subsidies, renewable energy can be employed for EV-charging at rates with a renewable mix premium of around 38% (2012) - 55% (2009) as compared to the general average rate costs. When compared to the optimal charging under the dynamic EEX-rate the cost difference still amounts in every case to more than 77%. This comparison disregards the fact that EEX-rates are lowered as the national renewable energy generation increasingly covers for a higher share of demand and thus makes power plants with lower marginal costs the price setting units (Sensfuss et al., 2008).

The analyses in this section show that uniform price based charging coordination can help to increase the individual decentral utilization of renewable energy, but might also encounter problems of overcoordination.

5.4 Discussion and Summary

Sections 5.2 and 5.3 provided insight about main questions concerning the ability of EVs to map and balance fluctuating generation patterns in such a way that the amount of conventional generation is minimized. They address EV demand flexibility in two similar settings which are coined by a supply side perspective. First, the ability to schedule the demand of a given fleet of EVs with empirical driving profiles of employees and retirees to available renewable generation was assessed by the implementation of a centralized benchmark scheduling approach. Second, the ability to perform the similar task in a decentralized manner only being coordinated by a uniform variable price mapping the available renewable energy, while assuming rational self-interested cost minimizing EVs, was evaluated. The results show that under the given assumptions EVs have a considerable demand flexibility which can be employed to maximize the real-time utilization of fluctuating renewable energy sources and thus enable sustainable electric mobility.

Renewable Energy Utilization Rate

Since it is one of the prevalent and less cost intensive renewable energy sources, wind power was chosen for the reference scenarios with respect to the ability of EVs to utilize this intermittent generation source. In addition, both sections evaluate PV and an evenly mixed portfolio of PV and wind power. In the benchmark approach it can be observed that employees can utilize up to 84.0% of wind power in their average yearly charging demand if charging is performed at home at 11 kW. Retirees in turn can utilize 79.7% of wind power on average over the year under the same conditions. These optimal values are not substantially affected if charging powers are reduced. A mixed generation portfolio with 50% wind power and 50% PV yields the highest overall adoption rate with 86.9% of yearly demand for employees being covered. The PV only generation in turn yields the lowest values with 61.3% - 65.9% in the same case.

The uniform pricing individual optimization approach also shows that employees can achieve a higher utilization rate than other sociodemographic groups. With a value of 48.0%, the overall level of wind power utilization on average over the year is still considerably lower than in the benchmark case. As the generation data basis is similar, only with slight scaling differences to fit the demand of the EVs, the reasons for this deviation must be clarified. Lower charging powers in the uniform pricing scenario increase the adoption rate of renewable energy as they force EVs to better distribute their demand over time. At the same time a mixed generation portfolio takes advantage of the complementary seasonal generation patterns of wind power and PV. The overall highest value of covered demand for the EV fleet is achieved in the mixed portfolio 1 kW case. Even though the demand basis is not completely comparable between the two analyses, the indication remains the same. It can be observed that PV achieves better values in the uniform pricing scenario (55.8% (3.6 kW) - 68.6% (1kW)) as more coordinated demand peaks that would otherwise overcompensate available renewable generation capacity can be covered by this likewise peaking form of generation.

This shows that the price communicated to individual vehicles needs to incorporate an adequate scarcity signal of the available capacity. This signal is not necessary in the benchmark case, but in turn more information about the planned trips of the entire fleet is needed. As observed in the computational analysis not all problem instances might be feasible in a centralized optimization approach without further adaptations.

Overall it can be concluded that EVs have a substantial flexibility potential to utilize fluctuating renewable sources, which could be harvested to some extent by a centralized coordination mechanism. This problem becomes infeasible or demands for more complex solutions in the presented fleet setting. The decentralized decision is therefore easier to implement but requires regional information about the remaining resource availability in order not to produce new coordinated peaks in the power system.

Charging Power and Location Impact

In the benchmark scenario charging power has no substantial impact on the RES utilization rate in the optimal Smart Charging cases. This is demonstrated for both the weekly and daily optimization horizon. If information about trips is available, charging can be coordinated in such a way that lower rates still enable the same adoption rates as in the 11 kW case. In the uniform price analysis in turn, charging power has a significant impact on the adoption rate that can be achieved. Charging at 11 kW (25.96%) and 3.6 kW (40.3%) for instance leads to even lower RES utilization rates than the uncoordinated charging approach (47.9%). This is due to the similar price information about available resources which is used by each individual EV to perform its charging optimization. For both scenarios one can observe that lower charging powers are more beneficial for higher RES utilization rates in the uncoordinated AFAP case as it distributes demand over a longer period of time, thus increasing the likelihood for fluctuating sources to be available. This effect can also be observed in the uniform pricing scenario for lower charging powers which can better concentrate the existing demand around the generation maxima. The higher adoption rate though comes at the cost of less feasible driving profiles. The infeasible profiles lack the time flexibility to charge for extended periods between their respective trips (e.g. employees lose 43% of the profiles due to these circumstances, cf. Table 5.13).

Additional charging opportunities at work and leisure locations (e.g. public charging stations) have a more substantial effect on the adoption of renewable energy. The strongest impact can be observed for employees that charge from PV only and are enabled to charge at work (increase between 6.7% - 7.1%). For retirees this effect can also be observed but is not as substantial (increase between 1.7% - 4.5% in absolute terms). Additional charging infrastructure can thus increase the adoption of PV in the charging supply. The main determinant for RES adoption still remains a reliable assessment of trip energy requirements.

Overall it can be concluded that higher charging powers increase the individual flexibility of an EV-owner; at the same time they are not necessary to achieve a good utilization of renewable energy sources if trip energy requirements are well-known. Then lower charging powers achieve similar results with respect to the utilization ratio. This finding shows that smart charging can also mean to charge at lower rates, which benefits both the power grid assets and the battery life time of the vehicle. Additional locations contribute to a better distribution of demand and can help to integrate PV better in the supply of EVs. In addition, they increase the availability of EVs on the grid which is also beneficial for a higher flexibility of the demand side.

Driving Profile Group

In particular the driving profile or sociodemographic group determine the driving distance and the availability of EVs at particular locations. Full time employees have about double the driving energy demand on average terms than retirees. These two groups are the most contradicting ones with respect to their general driving patterns and distances. In addition they represent 68.3% of the mobility patterns in the MOP and about 67.2% of the German population as of 2007 (BMVBS, 2008). Part-time employees and unemployed in turn resemble a differently weighted mixture of these groups (cf. Table 5.13, Appendix E).

Employees do not have such a high availability at the most accessible home charging location, which in particular deprives them of the possibility to cover similar high amounts of their demand from PV as retirees. This was discussed above and can be observed in the benchmark scenario analysis. Retirees in turn have a higher relative availability at the home charging location and thus a higher ground level of their demand which can be covered by PV. Retirees can however encounter the problem that their overall lower demand also leads to slightly lower adoption rates of RES. Due to the scenario assumptions (in particular the conventional generation constraints) a higher share of their demand is covered from conventional sources in order to fulfill the given constraints. In the uniform pricing scenario it can be observed that retirees can not take advantage of their substantial charging time flexibility as they concentrate their (in relation to employees) lower demand in times of relative high generation. The sketched overcoordination phenomenon leads to the fact that less demand, which would otherwise be more flexible, is concentrated again. This underlines the need for a regional scarcity signal for generation capacity.

It can be concluded that employees are likely to have higher adoption rates of renewable energy than other groups if technical constraints are considered. Their potential is also improved by charging infrastructure at their work location. Retirees and the other groups in turn can achieve higher adoption rates when only the home charging location is available for EVs. A generation mix of both fluctuating sources leads to the best results w.r.t. the direct utilization ratio as it helps to distribute demand better while the interday charging flexibility of EVs supports short term output variations.

Critique and Further Research Opportunities

The presented analyses both assume securely known values for their input data. This makes the results obtained an upper benchmark for the adoption potential of fluctuating sources by EVs in the respective scenarios. A shorter optimization horizon that does not require as much prior knowledge as assumed to be available, will lead to a more realistic assessment. For the benchmark scenario this analysis was performed and showed that still considerable parts (i.e. more than 60%) of demand can be covered by renewable sources. Moreover, this analysis does not account for the stochastic nature of the applied generators or spontaneous and irregular trip patterns. Nevertheless, it shows that the value of information about trip behavior for the next 1-3 days is crucial in order to coordinate the demand requirements with the expected variable supply sources.

The uniform pricing signal only incorporates the overall availability of renewable energy in its pricing pattern. The additional availability component slightly ameliorates the effect observed if all individual EVs perform their optimization without taking into account the remaining generation capacity. Nevertheless, new demand concentrations can be observed as a consequence of synchronized load behavior. In reality some of this load synchronicity will be diminished by stochastic elements in the demand and generation patterns, but this still shows that a decentralized charging coordination mechanism must set the right signals and incentives for EVs to shift their demand such that regional grid constraints and trip requirements are met. A local price component that maps the available capacity could be a possible solution to this challenge, following the approach of Schweppe et al. (1988) or the related implementation in Flath et al. (2013).

In this context the assessment of EV load flexibility in the individual context will also highly impact the results w.r.t. the ability to directly utilize renewable energy sources for EV charging.

Chapter 6

Summary and Conclusion

The transformation of the power system architecture from a centrally organized and operated system to a decentralized Smart Grid with a high share of volatile renewable generators requires the activation of demand side flexibility potentials. The thesis at hand investigated the demand response capabilities of EVs from different perspectives. Chapter 2 provides a comprehensive overview of the power system structure, the role of power markets and demand response in this context with a focus on EVs as a promising flexible load utilizing its demand shifting capabilities. Subsequently Chapter 3 specifies the research scenario and the methods employed within this thesis. In particular the role of the EV aggregator and the mechanisms for charging coordination are introduced. Further on the empirical input data employed in the analyses as well as simulation as a method for research in power systems are described.

Building on these foundations, Chapter 4 investigates the economic implications for EV-owners that individually coordinate their charging actions given a centralized variable price. This price is based on the wholesale energy price or on other signals addressing the system peak load and the availability of wind-power. Additionally, the individual economic effect of a V2G operation strategy is quantified under endogenous consideration of battery degradation costs.

In Chapter 5 the capability of EV fleets to map a given intermittent generation pattern and capacity is assessed under consideration of different optimization time frames. The analyses to quantify the demand side flexibility of an EV fleet differentiate between a central scheduling based upper benchmark approach, and a price based coordination mechanism enabling decentralized charging decisions. The findings and implications of these analyses are now condensed in the following section.

6.1 Contributions and Implications

The contributions of this thesis are elaborated according to the research questions formulated in Chapter 1. They are then discussed with respect to their implications on the power system and its regulation and finally, critically assessed under consideration of the inherent limitations of the employed approach.

6.1.1 Individual Economic Assessment of EV Charging Strategies

The individual costs for EV-owners are quantified as average costs per capita for the sociodemographic groups of employees and retirees. There are considerable differences in the economic outcomes of the analyzed charging strategies (cf. research question 1), given the variable pricing scheme as a basis for economic assessment.

The uncoordinated charging strategy (AFAP) is the least performing with respect to most applied evaluation measures. AFAP incurs the highest average costs per week ranging within 8.42 - 9.47 EUR (0.17 - 0.24 ct/kWh) for employees and 4.44 - 6.19 EUR (0.17 - 0.24 ct/kWh) for retirees. These costs are due to the fact that charging occurs during the rather high priced late afternoon and evening hours. Even though this strategy is the most expensive and has the potential to globally increase the system peak load, the demand of EVs is distributed fairly well during the week. As this strategy does not consider anything else but the mobility requirements, it guarantees the maximum potential travel distance, but does not employ any of the demand shifting flexibility that EVs have.

The cost minimizing smart charging strategy (EEX) represents the best option with respect to individual economic outcome, as it shifts charging to the time intervals with the lowest prices. The results show that this strategy leads to average cost reductions per week between 32 - 72% for employees as compared to the AFAP case. For retirees the average savings range between 50 - 74% per week as compared to the AFAP case. The range of variation stems from varying assumptions about the variable price incentive available to the vehicles. This shows how important the development of the wholesale price spread and the regulatory framework regarding the accessibility of variable prices for end customers are. Even though from an economic perspective this option is best, the results hold in particular for early adopters of price sensitive charging strategies. A wide scale adoption of EVs will influence the price determination and lead to higher market prices, which will further deteriorate savings. In addition, centralized uniform price signals do not incorporate local distribution grid conditions and must thus be adapted accordingly as they considerably increase the temporal concentration of charging load.

An extension of the smart charging strategy allows for further cost reductions even under the consideration of moderate battery degradation costs[1]. This strategy not only shifts load to cost minimal times but takes advantage of arbitrage opportunities on the wholesale energy market by feeding energy back to the grid (research question 2). The average cost reductions for employees increase from 32% per week to 44% as compared to AFAP if V2G operations are permitted. For retirees the savings increase from 50% per week to 61%. The results are promising as this part of the analysis incorporates current German power market regulations, and still demonstrates the financial profitability of a V2G strategy. Nevertheless, the results are sensitive to assumptions about battery degradation cost development and the further development of the wholesale market price spreads. In particular the merit order effect can be detrimental for this operation strategy of EVs as it reduces the amount of hours with high market prices. Apart from that, negative price events[2] induced by high wind and solar feed-in at low load, could be an opportunity that creates incentives for V2G strategies in the future. The increased volatility in the generation sector is likely to demand for more flexible generation resources, a requirement that EVs are able to meet (Andersson et al., 2010).

Coordinating the charging process according to the system load factor mostly resembles a conventional dual charging strategy, with charging during the night. In addition the load of this strategy is often concentrated at the weekly load factor minimum on early Sunday mornings which can be problematic if EVs are not distributed throughout the power grid. The savings are lower than in the cost minimizing strategy and amount to 63% for the employees and 66% for the retirees as compared to AFAP. Since the global system condition might be contradictious to the local capacity constraints this charging strategy does not appear to have any substantial advantages, neither for the power grid nor

[1]These results refer to the reference scenario with 0.1 EUR/kWh energy related and 0.01 EUR/kWh^2 power related battery degradation costs, and include infrastructure costs.

[2]Between 2008-2012 there was an average of 46.8 hours in the year with negative prices on the EEX (EEX, 2013).

for the EV-owner.

The residual charging strategy is sensitive to the overall system load factor but also considers the availability of higher shares of wind-power. From a cost perspective it is similar to the load factor strategy and also generates average savings of 64% for employees and 65% for retirees as compared to AFAP. The ability to react to higher shares of wind-power in the system makes this strategy a fairly good option, including multiple criteria in its coordination objectives. Since it adopts more wind-power in the average yearly demand as the cost minimizing, load factor, and AFAP strategy, it constitutes a good operational compromise. Even though the strategy is advantageous, it must consider local constraints for its further application.

Coordinating EV charging according to the relative share of wind-power in the system can increase the average yearly share of wind-power in the EV demand from around 7% for AFAP to 14% for employees and 15% for retirees. This improvement in wind-power utilization comes at higher costs than in all other smart charging strategies, but still achieves average savings of 48% for employees and 49% for retirees as compared to AFAP. These results show that the integration of wind-power into the charging demand is not adequately incentivized by the currently applied market conditions. The merit order effect and an increasing share of volatile generation (e.g. PV) have the potential to improve this situation if they are accounted for in further developments of a RES-oriented charging strategy.

In conclusion it can be said that smart charging is indeed worthwhile in the investigated scenarios. EVs that are responsive to price incentives or other charging signals have the potential to substantially increase savings and share of utilized wind-power as compared to the case of no charging coordination. The consideration of energy and power related battery degradation costs supports these findings and suggests lower charging powers to further foster the grid integration of EVs.

6.1.2 Renewable Energy Integration Potential of EV Fleets

In order to quantify the demand flexibility of EVs, the ability of an EV fleet to shift its load in such a way as to closely map the volatile generation output of renewable sources and thus minimizing the reliance on conventional generation must be assessed. This analysis is performed from the perspective of an EV aggregator that schedules EV demand according to the generation output of wind and PV under consideration of mobility and conventional generation constraints for the time period of one week (research question 3).

The results of this scheduling approach present a benchmark with respect to the maximum renewable energy utilization potential. They show that employees which only charge at the home location have the ability to utilize up to 84% wind-power to cover their yearly demand, while retirees achieve 79% in the same scenario. As generation output is scaled to exactly meet the yearly EV-demand, the ability of the EVs to shift their demand is at the center of the analysis. The slightly lower utilization rate of retirees is mainly due to the conventional generation constraints which assume the same capacity and must run time constraints for both groups.

If PV is employed as the main source for charging of the distributed EV fleet it can be observed that the adoption rate is lower for employees with 65% of the yearly demand covered and 68% for retirees. Allowing for additional charging opportunities at work and leisure locations further increases these values to about 72% for both groups. The best adoption rate can be achieved by the evenly mixed generation portfolio of wind-power and PV, which yields a maximum of 86% for employees and 83% for retirees, under invariance against the charging location and applied charging power. AFAP in comparison only yields values between 19% (employee, 3.6 kW, home, PV) and 64% (retired, 3.6 kW, home+work+leisure, wind+PV). This implies that knowledge about the trip requirements is crucial to allow for an effective adoption of fluctuating energy sources in the electricity supply.

Since regular trip patterns are quite well known in advance (e.g., work trips) information about the availability of variable generation plays an important role. To account for uncertainty about the available renewable generation, a reduction of the optimization horizon to one day is performed. The results show that the share of renewable energy adopted is lower with 62% (wind, home) for employees and retirees with 64% (wind, home) than in the weekly optimization scenario. Maximum adoption is in the range of 74% (home+work+leisure, 11 kW, wind+pv) for employees and 77% for retirees. The daily optimization thus takes into account more accurate generation forecasts, but at the same time loses demand flexibility that exists between the different days as vehicles do not need to be recharged every day to guarantee mobility. In this context, accurate knowledge about the trip patterns for 1-3 days and the availability at the power grid is essential to unlock the full adoption potential for renewable energy. In the future, one should explore the possibilities to adjust trip requirements in order to exploit the full RES adoption potential. With respect to generation sources and charging locations, it can be concluded that work charging is beneficial for employees with respect to PV utilization, and that leisure locations do not necessarily need to provide charging opportunities for either of the sociodemographic groups, since the bulk potential can be unlocked by home and work charging already.

If the flexible demand of an EV fleet is to be coordinated by a price signal based on the relative scarcity of renewable generation and the potential grid availability of the EVs, a decentral economic decision of every vehicle is possible. The results with respect to the price based coordination approach of an EV aggregator fleet (research question 4) show that a uniform price mechanism can produce new demand concentrations that overcompensate the available renewable generation capacity for the particular time interval. Over a year the adoption potential of wind-power for an evenly weighted EV fleet with 25% employees, retirees, unemployed and part-time employees is 40% of the yearly demand (home, 3.6 kW). Due to the new demand peaks, uncoordinated charging would perform better in this case with a share of 47% of yearly demand covered. In order to increase the RES adoption share, the charging power can be lowered, e.g., to 1 kW. As before an even mix of PV and wind-power can be employed to supply the vehicles. This yields a maximum of 75% of EV demand covered by renewable sources. This increase however comes at the cost of less feasible driving profiles since the charging power does not suffice in particular for about 19% of the employees to cover their mobility requirements. The uniform price based coordination must be thus altered to include a local, or in this case, a renewable capacity feedback mechanism that dynamically incorporates the scarcity of renewable generation still available in one time interval.

A further economic analysis shows that even if the capital costs for a contracted wind power plant are included the average offering price for the aggregator, or in particular the costs for the EV-owner, based on cost and price data for 2009, is near the average end-consumer price for this year. In particular the aggregator could offer wind power including all fees at around 23.19 ct/kWh, while the average price for 2009 was 22.82 ct/kWh for end-consumers. For an exclusive PV offer the costs would be considerably higher at 2009 price values with an average price level of 47.43 ct/kWh. The substantial cost reductions in recent years dramatically improve the offer for PV only supply, but would still make it an expensive option. If a customer would instead choose a variable supply based on the wholesale price for 2009 his costs would only approach the region of 14 - 15 ct/kWh. Since the situation with respect to levelized cost of electricity from PV has developed quickly in recent years, the economics of autonomous PV based supply have improved, making a local utilization of electricity PV financially viable and worthy of further investigations.

Overall this thesis shows that EVs have the potential to cover substantial amounts of their demand from volatile sources, and that they can do so at only low additional costs. In order to support a decentralized charging decision local grid capacity and renewable generation potentials must be accounted for in the respective price incentives.

6.1.3 Limitations of the Approach

The simulation-based analysis is dependent on the quality of input data and the assumptions made about the research scenario. This work mostly employed real world data in particular for driving profile characteristics and generation, as well as price patterns. Nevertheless, uncertainty is not explicitly accounted for in most of the analyses. Instead, several sensitivities with respect to the availability of charging locations and different pricing regimes were investigated. Future work thus needs to address the impact of the inherent uncertainty that exists about driving profiles and renewable generation patterns on the optimization objectives. Price uncertainty also exists, but has a lower impact in markets that have a reference price which is determined in an auction for every time interval of the following day. This could change if additional locational price components are considered in future regional power markets (Schweppe et al., 1988). Shorter optimization horizons and stochastic optimization methods (e.g., rolling horizon approaches) should thus be addressed by further studies of EV demand flexibility. The assumptions about fleet size, technical specifications of the vehicles and generation capacity dimensioning were made in such a way that they represent reasonable, real world problem sizes and instances. The instances chosen represent the most relevant groups and account for a likely development with respect to intermittent generation sources and power market regulation when it comes to the availability of variable prices for end consumers.

6.2 Further Research Opportunities

This thesis concentrates on EVs, but further work must also consider the interaction with other (flexible) loads and the local generation capacity in order to allow for an integrated assessment of EVs and their demand response capabilities. A possible approach would be to first include unresponsive conventional loads like households (cf. Gottwalt et al. (2013)); further steps should then investigate the interaction with an increasing share of responsive loads (e.g. air conditioning, domestic water heating or heat pumps) and quantify the abilities of EVs in relation to other load types. Further application of the evaluated coordination strategies to other flexible loads could also be a promising extension of the presented work, since more than the potential load flexibility of EVs is required to support the realization of the "*Energiewende*" in the power sector.

Starting from the demand side flexibility of EVs, the quantification of load flexibility must be further pursued in order to unlock the full potential that Smart Grid technology is able to deliver. For this, the increasingly available amount of smart metering load and generation data can be scrutinized with respect to common consumption patterns and the derivation of load shifting potentials. The strategies developed in this thesis could be further integrated in a decision support system based on this data, helping end-customers to make more informed decisions about their daily energy consumption and thus support the development of an effective demand response capability.

The development of the regulatory framework needs to support more decentralized decisions and system operation, and must potentially be adapted to respond to structural changes imposed by the large numbers of distributed energy resources and adaptive loads like EVs. Since centralized solutions are not capable to address the complexity imposed by the variability and the distributed nature of the envisioned Smart Grid, decentralized coordination mechanisms must be further investigated and validated in regional markets under consideration of the inherent uncertainty in this environment (Ramchurn et al., 2012). The presented coordination approaches are likely to be applied by EV owners and EV aggregators and could, through further development to a large scale scenario, support the assessment of regulatory design decisions for the power market regarding these roles.

Even though the Smart Grid is predominantly a techno-economical concept, the integration of the user must occur in an appropriate manner. In this context, the elicitation of user preferences and their accurate representation by automation technology is crucial for the efficient implementation of demand response mechanisms. Only through active, safe and privacy supporting consumer participation, the Smart Grid paradigm can truly deliver its envisioned promises.

Appendix A

List of Abbreviations

AC	Alternating Current
AS	Ancillary Services
BEV	Battery Electric Vehicle
CAISO	California Independent System Operator
CCGT	Combined Cycle Gas Turbine
CCP	Critical Peak Pricing
CV	Coefficient of Variation
DC	Direct Current
DR	Demand Response
DER	Distributed Energy Resource
DSM	Demand Side Management
DSO	Distribution System Operator
EEX	European Energy Exchange
EPEX	European Power Exchange
EDV	Electric Drive Vehicle
ESP	Energy Service Provider
EV	Electric Vehicle
FC	Fuel Cell
FCEV	Fuel Cell Electric Vehicle
HEV	Hybrid-Electric-Vehicle
ICE	Internal Combustion Engine
ICEV	Internal Combustion Engine Vehicle
ISO	Independent System Operator
MOP	Mobility Panel Germany
NHTS	National Household Travel Survey
PEMFC	Proton Exchange Membrane Fuel Cell
PLC	Power Line Communications
PHEV	Plug-In-Hybrid Electric Vehicle

PV	Photovoltaics
RTP	Real Time Pricing
RTO	Regional Transmission Operator
SOC	State of Charge
TOU	Time-of-Use
TRY	Test Reference Year
TSO	Transmission System Operator
UC	Unit Commitment
VPP	Virtual Power Plant

Appendix B

List of Symbols

C	Usable capacity of the storage device
d_t	Energy consumption in time slot t
g_t	Total generation in time slot t
$g_{t,I}$	Intermittent generation in time slot t
$g_{t,C}$	Conventional generation in time slot t
$\overline{g_{t,C}}$	Maximum conventional generation in time slot t
l_t	Total load in time slot t
v^c	Number of time slots to charge at max. power
η^c	Charging efficiency in % of initial input
p_t	Price of electricity in time slot t
$p_{t,C}$	Price of conventional generation
$p_{t,R}$	Price of renewable generation
ψ	Storage costs
r_t	Rank of hour t
φ_t	Charge parameter for time slot t
z_t	Location of the EV, i.E. charging availability

Appendix C

EV Technology and Storage Components

EV Drive Train Concepts and Grid Connectors

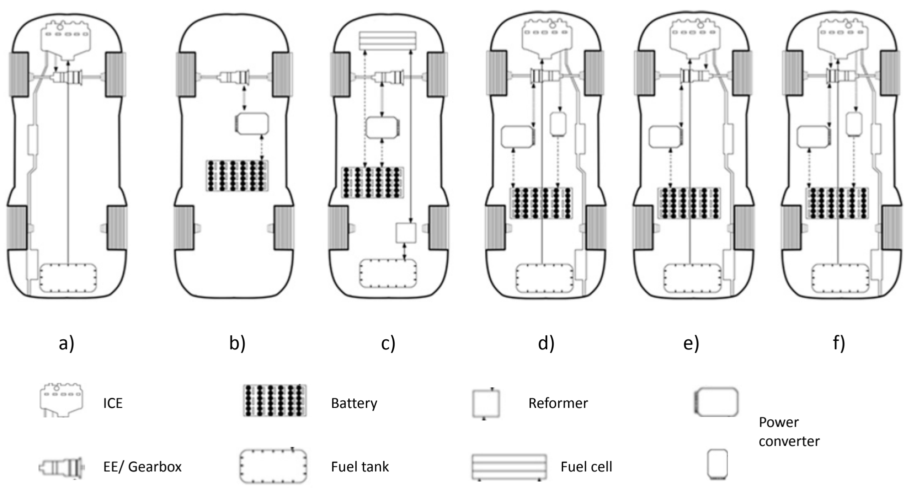


Figure C.1: Schematic representation of different vehicle drivetrain concepts: a) Conventional ICEV, b) EV, c) FCEV, d) Series-Hybrid, e) Parallel-Hybrid, f) Series Parallel Hybrid, adapted from Pollet et al. (2012).

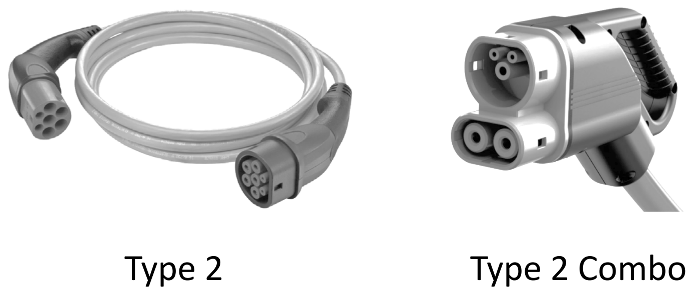


Figure C.2: Type two connectors for Europe, and the standard connection in Germany according to IEC 62196-2 /3 adapted from NPE (2011a).

Figure C.3: Main EV connector types according to norm IEC 62196 for the US and Europe, adapted from (Phoenix Contact, 2012).

Table C.1: Specifications of Commercially Available Li-ion Cells from Several Manufacturers, from Reddy and Linden (2011).

Manufacturer	Cell	Average voltage [V]	Charge endpoint [V]	Capacity [mAh]	Diameter [mm]	Length [mm]	Volume [mL]	Mass [g]	Specific energy [Wh/kg]	Energy density [Wh/L]	Positive electrode
Energy Cells											
Panasonic	NCR18650	3.6	4.2	2900	18.6	65.2	17.71	N/A	N/A	589.31	NCA
Panasonic	CGR18650E	3.7	4.2	2550	18.6	65.2	17.71	46.5	202.90	532.58	
Panasonic	CGR18650CG	3.6	4.2	2250	18.6	65.2	17.71	45	180	457.22	
LG Chem	ICR18650C1	3.75	4.35	2800	18.29	65.02	17.08	48	218.75	614.66	
Samsung	ICR18650-30A	3.78	4.35	3000	18.6	65.2	17.71	48	236.25	640.12	
Samsung	ICR18650-28A	3.75	4.3	2800	18.6	65.2	17.71	48	218.75	592.70	
Samsung	ICR18650-26F	3.7	4.2	2600	18.6	65.2	17.71	46	209.13	543.03	LCO/NMC
Samsung	ICR18650-24F	3.7	4.2	2400	18.6	65.2	17.71	45	197.33	501.25	NMC
Samsung	ICR18650-22F	3.7	4.2	2250	18.6	65.2	17.71	44.2	188.34	469.93	NMC
Sanyo	UR18650-ZT	3.7	4.3	2800	18.24	65.1	17.01	48	215.83	609.04	Hybrid(?)
Sanyo	UR18650-F	3.7	4.2	2600	18.1	64.8	16.67	47	204.68	576.98	
ATL	18650E	3.7	4.2	2150	18.4	65	17.28	45	176.77	460.27	NMC
Boston Power	Sonata 4400	3.7	4.2	4400	18.5	65.2	44.75	92	176.95	363.79	LCO
E-One Moli	IHR18650B	3.6	4.2	2250	18.4	65.2	17.3	47.5	166	457	NMC
Power Cells											
A123	APR18650M1 AHR18700M1	3.3	3.6	1100	18.4	65	17.3	39	93.07	210.02	LFP
A123	Ultra	3.3	3.6	700	18.4	70.0	18.6	38	61	124	LFP
Samsung	IFR18650-11P	3.2	3.6	1100	18.6	65.2	17.71	43	81.86	198.69	LFP
ATL	18650P	3.7	4.2	1380	18.4	65	17.28	45	113.46	295.43	NMC
E-One Moli	IMR18650E	3.8	4.2	1400	18.24	65	16.98	42	126.66	313.23	LMO
E-One Moli	IMR18650D	3.8	4.2	1530	18.4	65.3	17.7	44.5	133	344	LMO
E-One Moli	IBR18650B	3.6	4.2	1500	18	65	16.6	42	129	327	LMO/NMC

Energy Storage Process

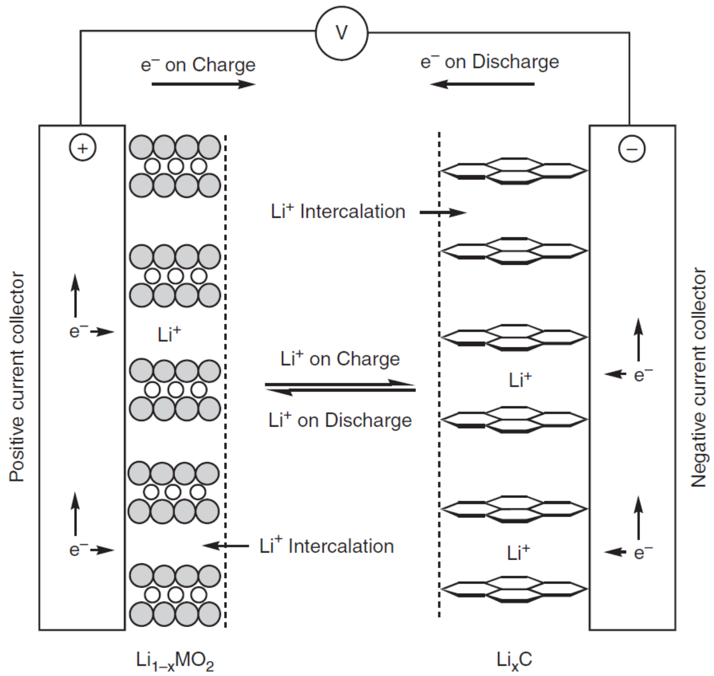
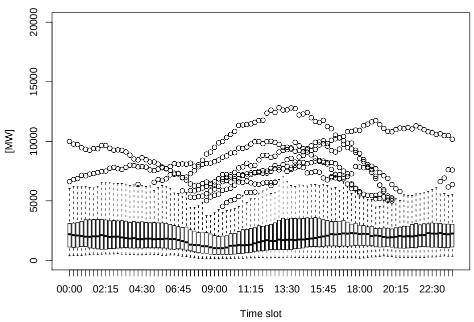


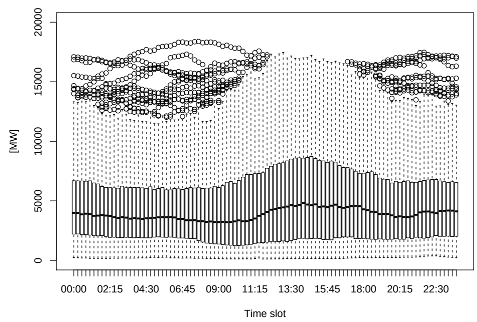
Figure C.4: General representation of the electrochemical process in a Li-ion cell (Reddy and Linden, 2011).

Appendix D

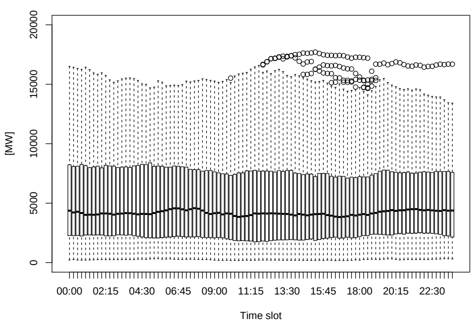
Renewable Energy Generation Data



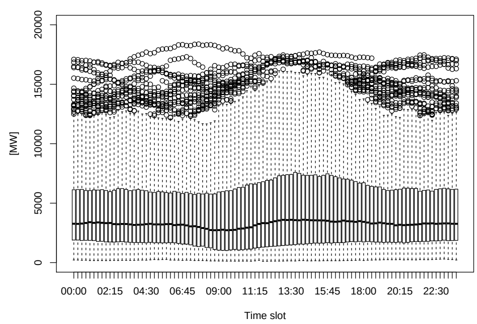
(a) 15 min. wind generation variation for summerdays



(b) 15 min. wind generation variation for transition days

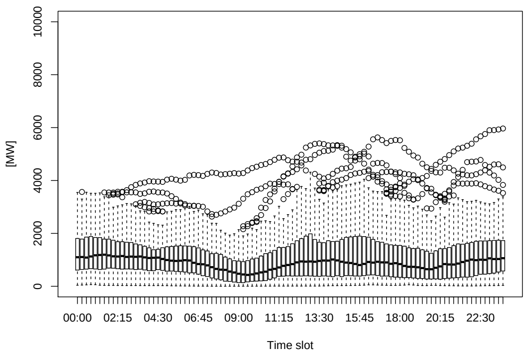


(c) 15 min. wind generation variation for winter days

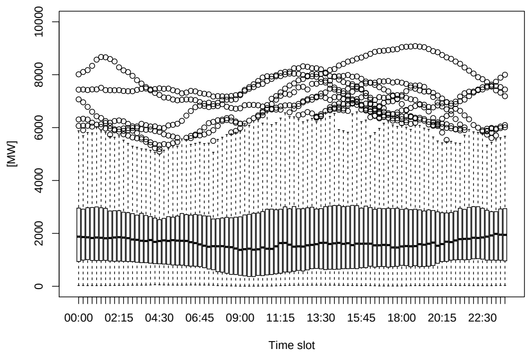


(d) 15 min. wind generation variation for all day types

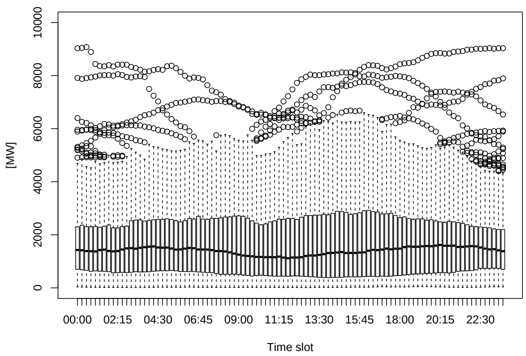
Figure D.1: Wind-power generation variation for all TRY day types for Germany for 2007, (EEX, 2009).



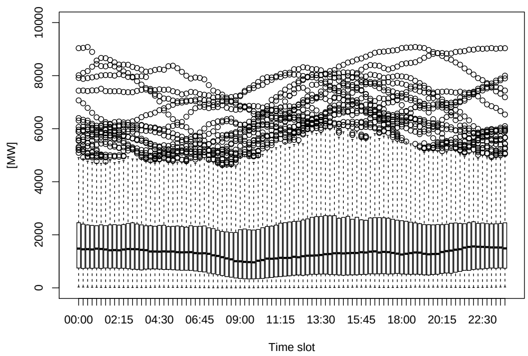
(a) 15 min. wind generation variation for summerdays



(b) 15 min. wind generation variation for transition days

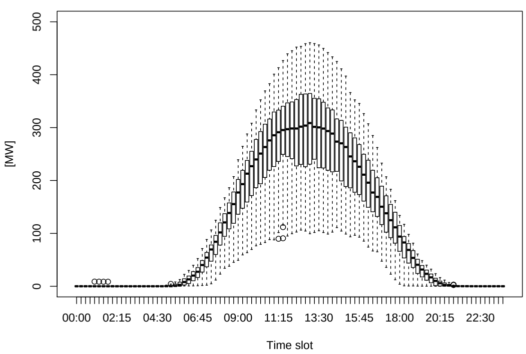


(c) 15 min. wind generation variation for winter days

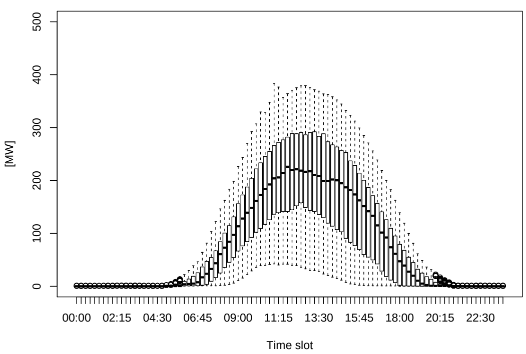


(d) 15 min. wind generation variation for all day types

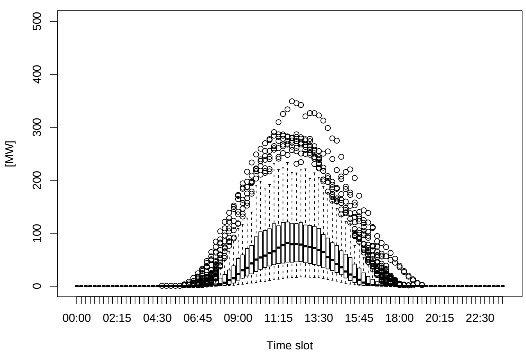
Figure D.2: Wind-power generation variation for all TRY day types from the 50 Hertz TSO-zone, (50-Hertz, 2010).



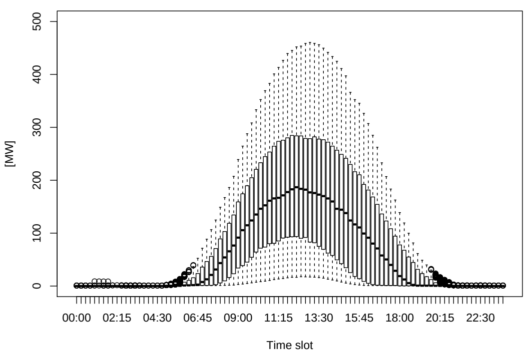
(a) 15 min. PV generation variation for summer days



(b) 15 min. wind generation variation for transition days



(c) 15 min. PV generation variation for winter days



(d) 15 min. PV generation variation for all day types

Figure D.3: Wind-power and PV generation variation for all TRY day types from the 50 Hertz TSO-zone, (50-Hertz, 2010).

Appendix E

Empirical Driving Patterns

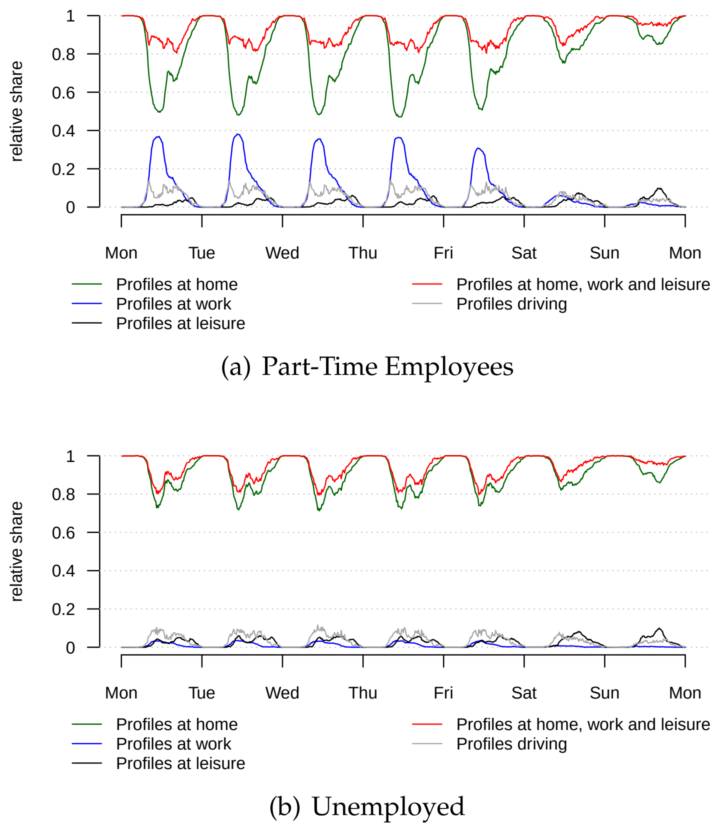
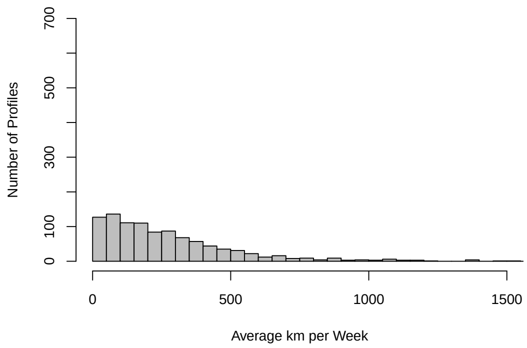
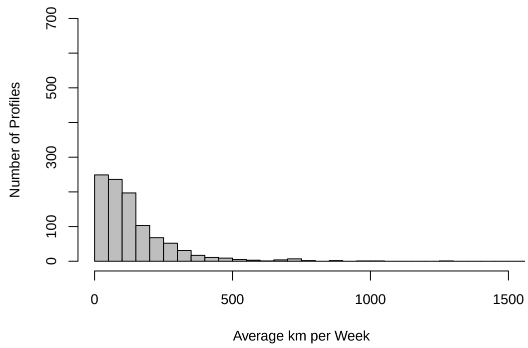


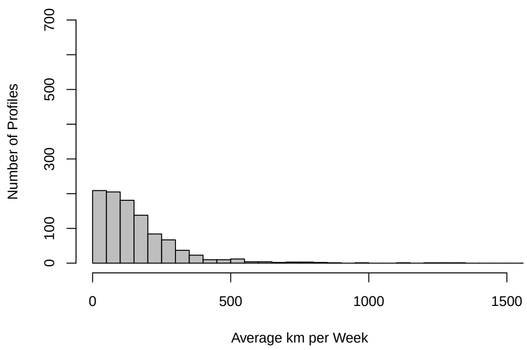
Figure E.1: Availability at home, work and leisure locations for part-time employees and unemployed over the course of the week.



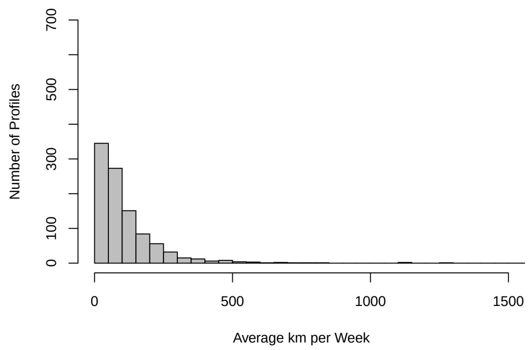
(a) Weekly distribution Employees



(b) Weekly distribution Retired



(c) Weekly distribution Part-time Employees



(d) Unemployed

Figure E.2: Distribution of profiles with respect to the weekly driving distance for all four sociodemographic groups.

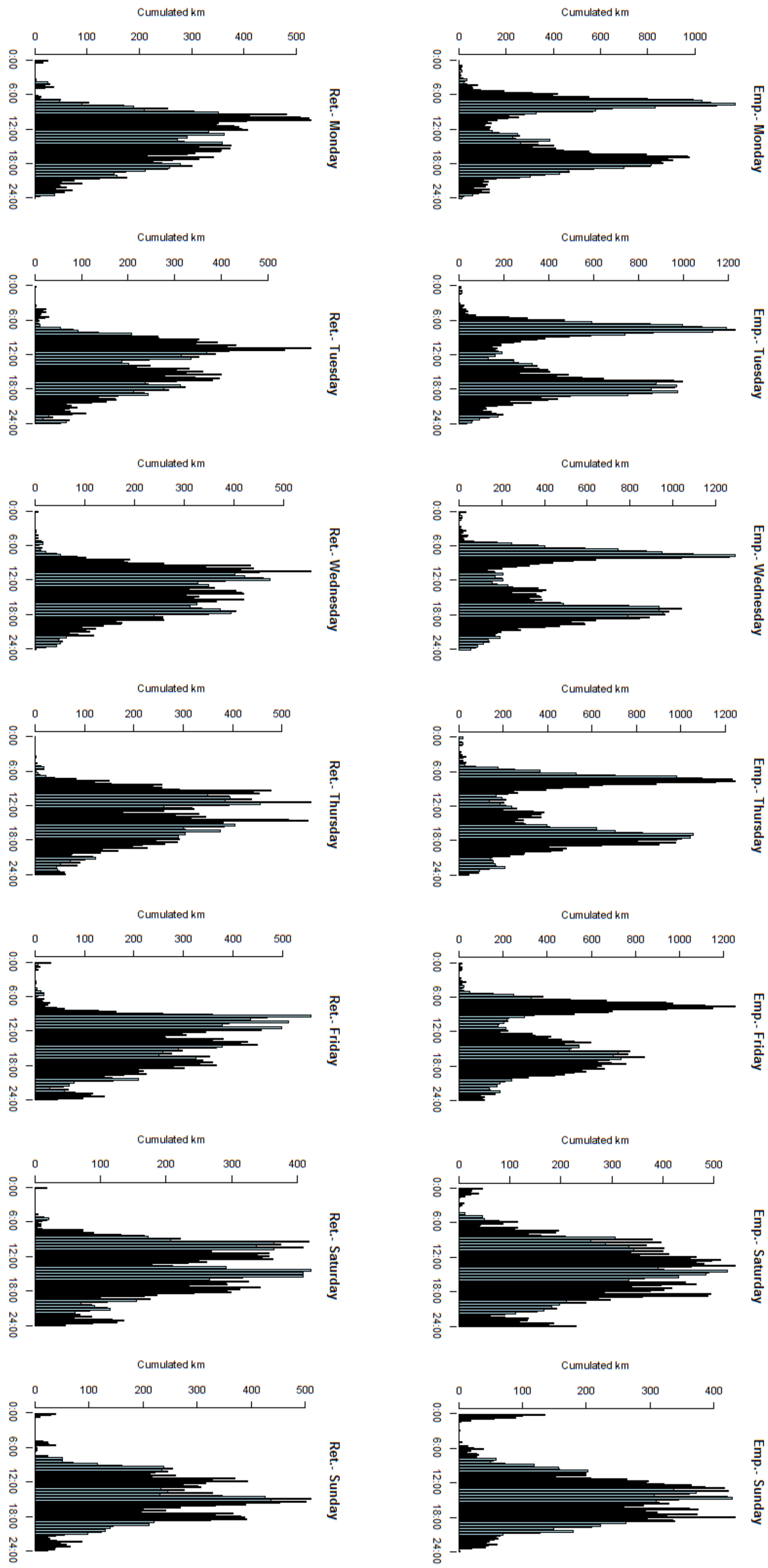


Figure E.3: Weekly driving pattern distribution for the group of 1000 employees and retired persons of the MOP that were employed for most of the analyses, BMVBS (2008).

Appendix F

Benchmark Model Formulation

```
// Benchmark Optimization Model Formulation in OPL

// Variable declaration
int NbPeriods = ...;
int NbVehicles = ...;

float maxConventionalGeneration = ...;
float minConventionalGeneration = ...;
float initSoc =...;
float maxSoc = ...;
float endSoc = ...;
float efficiency = 0.93;
float maxChargeAmount =...;

// Constant conventional generation costs in ct/kWh

float conventionalGenCost = 0.05;

range Vehicles = 1..NbVehicles;
range Periods = 1..NbPeriods;

float ChargingPossible[Vehicles][Periods] = ...;
float Demand[Vehicles][Periods] = ...;
float RG[Periods] = ...;


// Decision variables

dvar float+ PosChargeamount[Vehicles][Periods];
dvar float+ Soc[Vehicles][Periods];
dvar float+ CG[Periods];
dvar int isOn[Periods] in 0..1;  // integer variable
dvar int ramp[Periods] in 0..1;  // integer variable
```

```
//Objective function

minimize
sum( t in Periods )(
CG[t]*conventionalGenCost);


//Constraints:

subject to {

// Positive conventional generation max. capacity
forall(t in Periods)
ctConventionalGeneration:
RG[t]-(sum (v in Vehicles)PosChargeamount[v][t])/efficiency + CG[t]>=0;

// Convetional generation constraints
forall(t in Periods)
ctConventionalGenerationCapacity:
CG[t]<=maxConventionalGeneration*isOn[t];

// Minimum capacity requirement CG
forall(t in Periods)
ctMinConventionalGenerationCapacity:
isOn[t]*minConventionalGeneration <=CG[t];

// If CG is on, it has been on, or needs to be ramped to be on
forall(t in 2..NbPeriods)
ctRamping:
isOn[t]<=isOn[t-1]+ramp[t];

// Three time steps minimum run time constraints
forall(t in 1..NbPeriods-1)
ctRampingKeepOn1:
isOn[t+1]>=ramp[t];

forall(t in 1..NbPeriods-2)
ctRampingKeepOn2:
isOn[t+2]>=ramp[t];

forall(t in 1..NbPeriods-3)
ctRampingKeepOn3:
isOn[t+3]>=ramp[t];
```

```
// In the first timeslot the CG must be ramped to be on
ctRampingFirst:
isOn[1]<= ramp[1];


// EV constraints
forall(v in Vehicles)
ctInitStorage:
  Soc[v][1] == initSoc + PosChargeamount[v][1] - Demand[v][1];

forall(v in Vehicles, t in 2..NbPeriods )
ctStorageConstraint:
  Soc[v][t] == Soc[v][t-1]+ PosChargeamount[v][t] - Demand[v][t];

forall(v in Vehicles, t in Periods )
ctChargeamount:
PosChargeamount[v][t] <= ChargingPossible[v][t]*maxChargeAmount;

// Battery capacity constraint is the same for the entire fleet
forall(v in Vehicles, t in Periods )
ctMaxSoc:
Soc[v][t] <= maxSoc;

forall(v in Vehicles)
ctEnd:
Soc[v][NbPeriods] == endSoc;

// SOC is always positive
forall(v in Vehicles, t in Periods )
ctNonNegativeSoc:
Soc[v][t] >= 0;

forall(t in Periods)
ctNonNegativeCG:
CG[t]>=0;

forall(v in Vehicles,  t in Periods)
ctNonNegativeChargeamount:
PosChargeamount[v][t] >= 0;

};
```

Appendix G

Computation Time Analysis

The following figures give an impression of the simulation times in the benchmark simulation model case. In addition the details of the employed main hardware for simulations and the main software packages used are reported.

Main Simulation Machines:

- Intel(R) Core(TM) 2 Duo CPU T9400 2.53 GHZ, 4 GB RAM, Windows 7 Enterprise, 64 bit.
- Intel(R) Core(TM) i7-2620M CPU @2.70 GHz, 8 GB RAM, Windows 7 Professional 64 bit.
- AMD Phenom(tm) II X6 1055T Processor 2.80 GHz, 16 GB RAM, Windows 8 Pro 64 bit.

Main Software:

- Java Versions: 1.6.21-24, 1.7.0-11
- Optimization Engine: IBM Ilog CPlex 12.4.0.0 (Chapter 4.2 and 5.1), lp-solve 5.5.0.2 (Chapter 4.1 and 5.2)
- Evaluations and Graphs: R 2.14.2 and previous Versions, R Studio version 0.97.309, Matlab Version 7.10.0499(R2010a)

Comments on the Computation Time Analysis

Following the trends depicted in the Figures below one can observe that computation time is particularly increasing in situations in which the solution space for the optimization problem is increased. This can be achieved in particular by lower charging powers, in conjunction with additional charging locations. Also the PV scenarios are observed to be the ones with the highest overall per day or per week computation times. The most extreme case occurs for retirees in the home only PV case with 3.6 kW G.15. In this particular setting the computation of the optimal schedule for one day takes substantially longer than one day to compute which makes an operative decision in a day ahead setting impossible. Therefore a reduction of the optimality criterion must be considered in such cases.

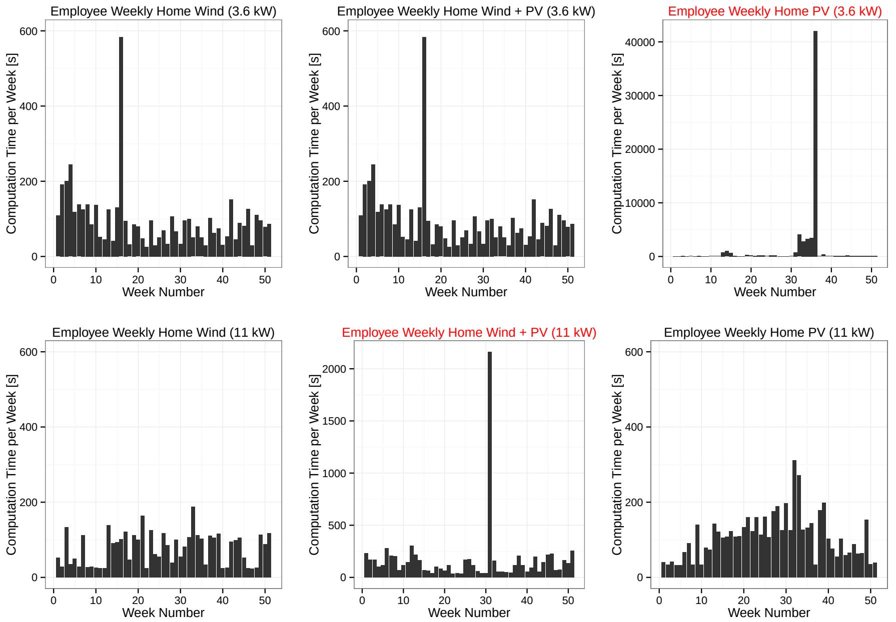


Figure G.1: Computation times overview for the optimal benchmark case for employees in the weekly optimization home charging scenario.

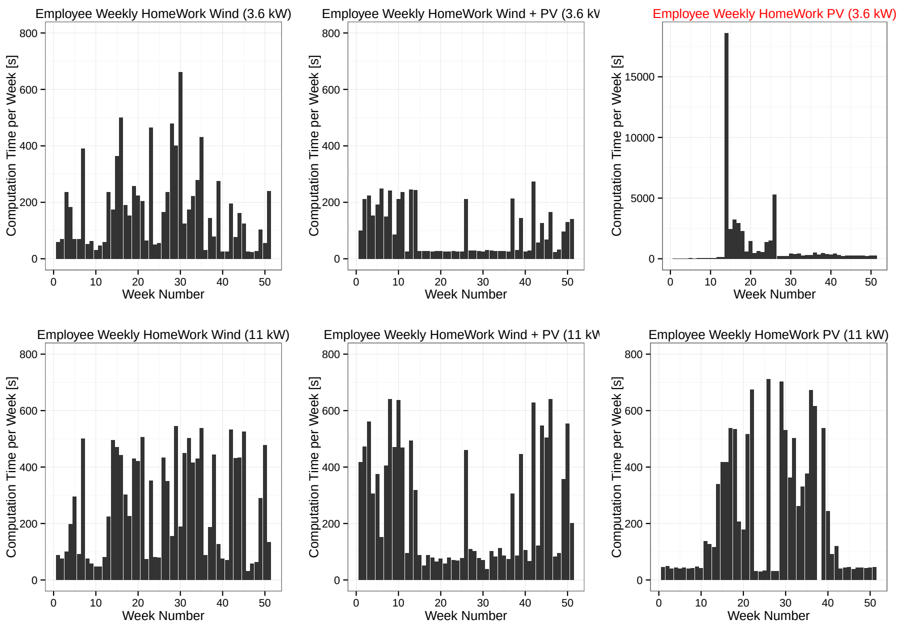


Figure G.2: Computation times overview for the optimal benchmark case for employees in the weekly optimization home + work charging scenario.

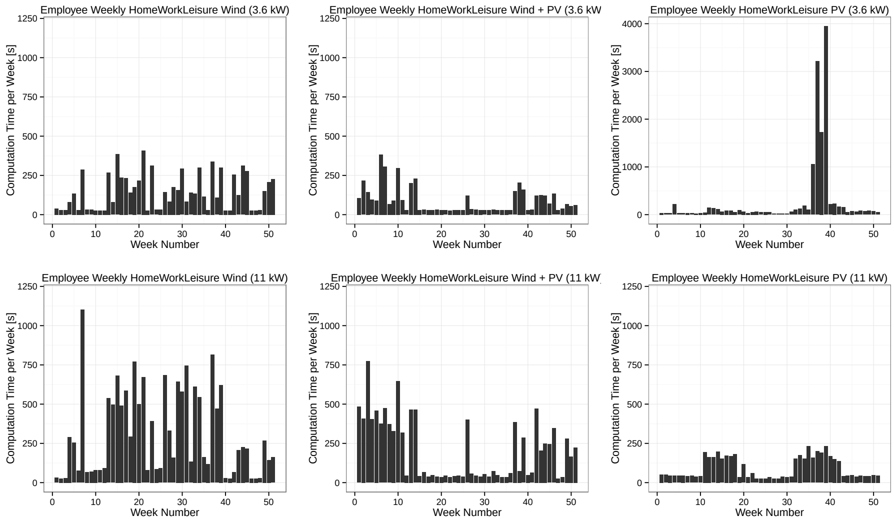


Figure G.3: Computation times overview for the optimal benchmark case for employees in the weekly optimization home + work + leisure charging scenario.

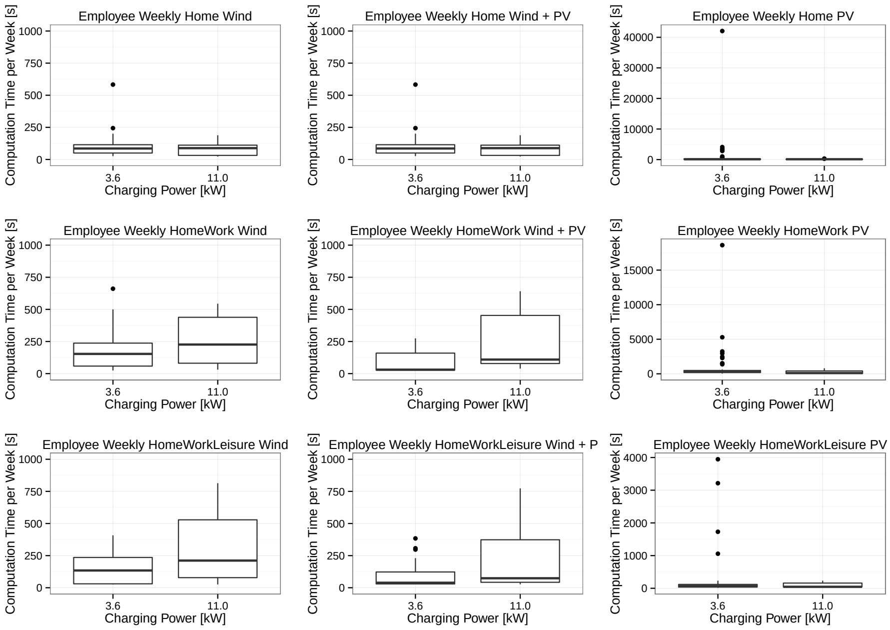


Figure G.4: Variation of computation times for the optimal benchmark case for employees in the weekly optimization scenario.

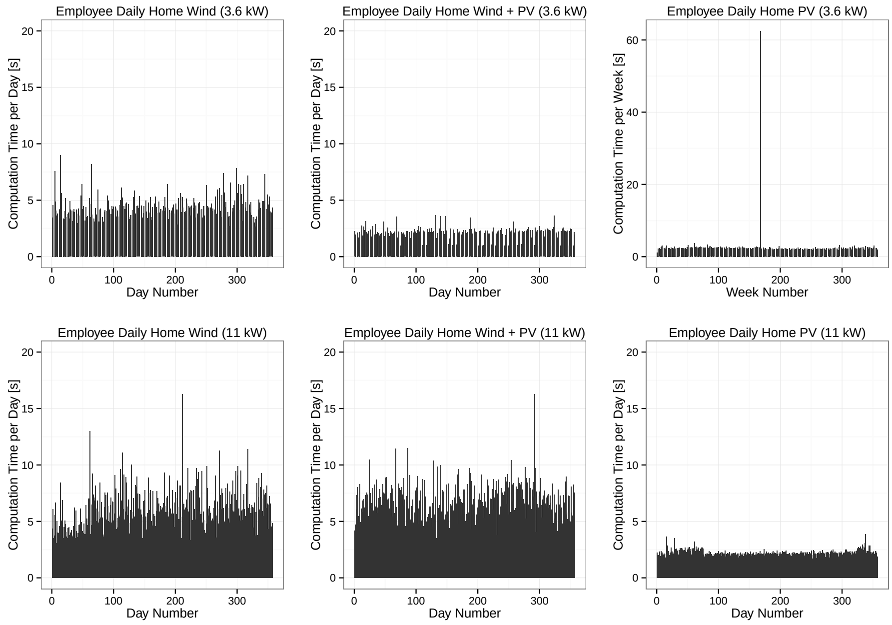


Figure G.5: Computation times overview for the optimal benchmark case for employees in the daily optimization home + work + leisure charging scenario.

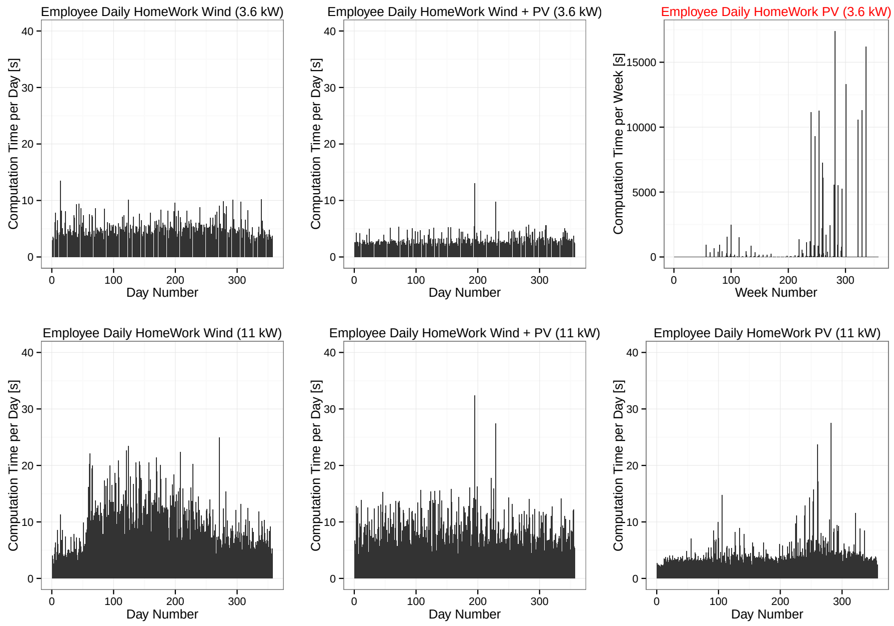


Figure G.6: Computation times overview for the optimal benchmark case for employees in the daily optimization home + work + leisure charging scenario.

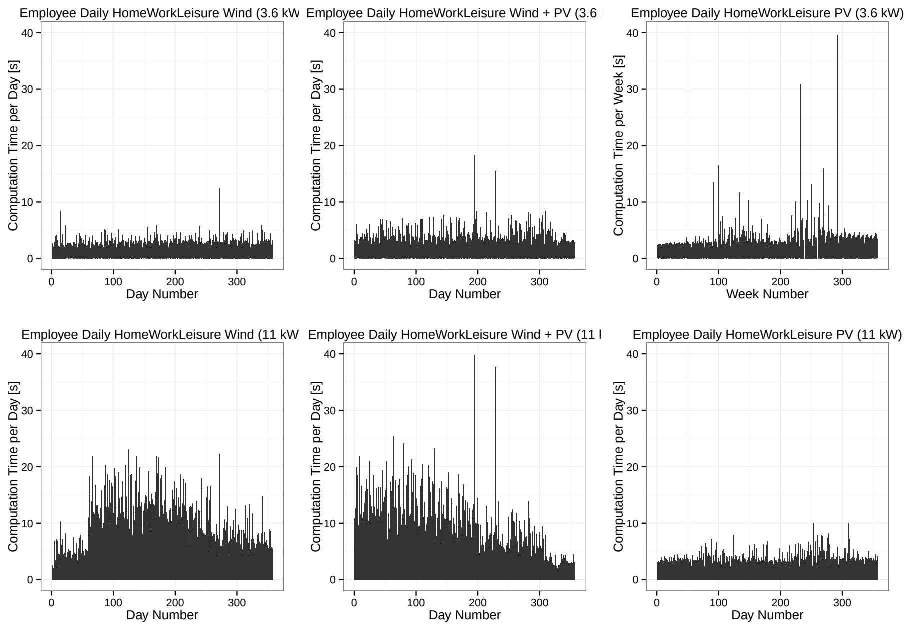


Figure G.7: Computation times overview for the optimal benchmark case for employees in the daily optimization home + work + leisure charging scenario.

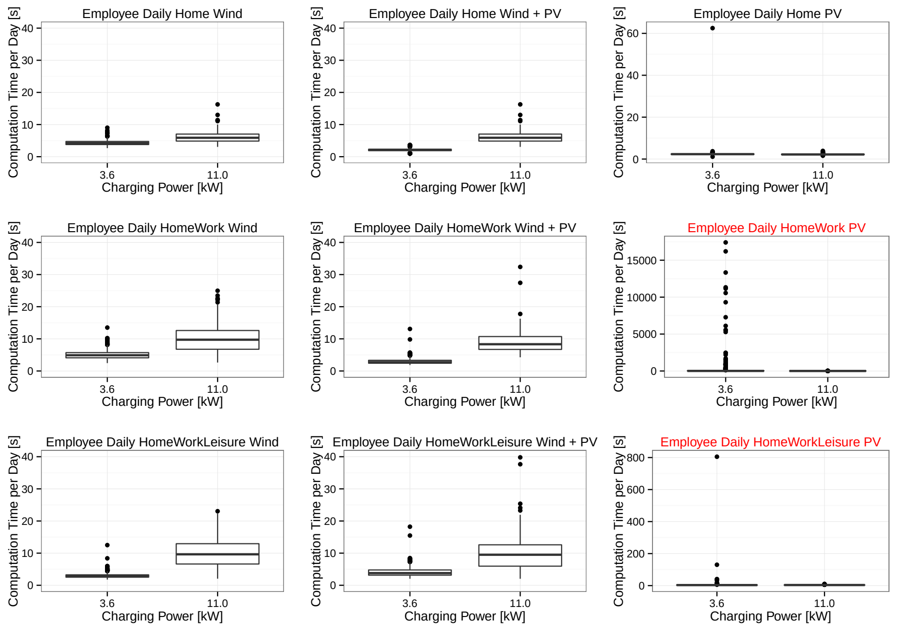


Figure G.8: Variation of computation times for the optimal benchmark case for employees in the daily optimization scenario.

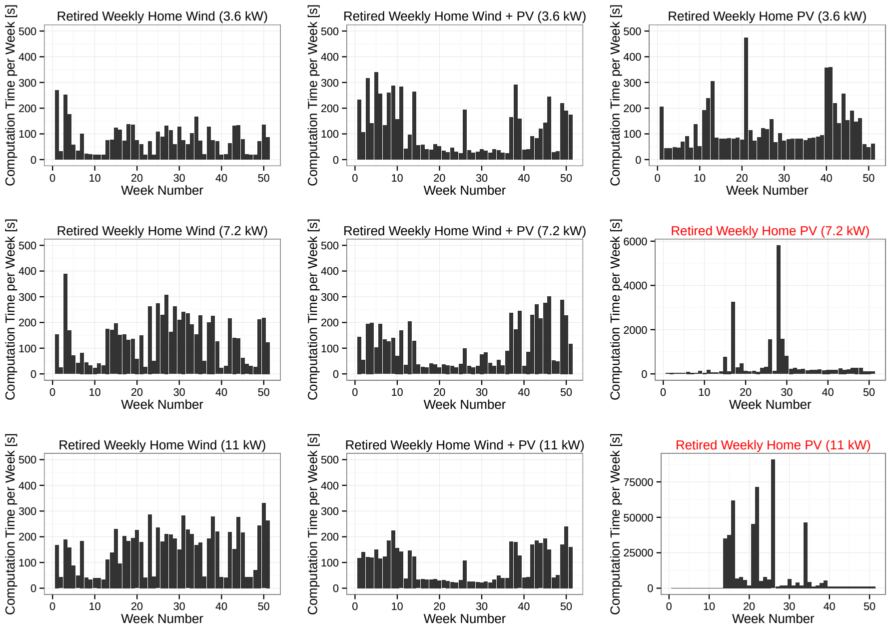


Figure G.9: Computation times overview for the optimal benchmark case for retirees in the weekly optimization home charging scenario.

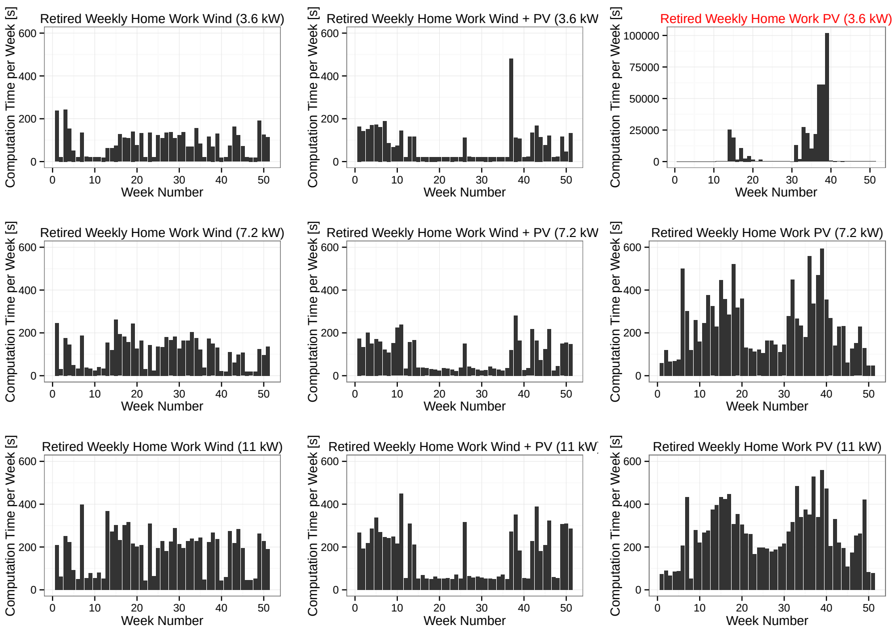


Figure G.10: Computation times overview for the optimal benchmark case for retirees in the weekly optimization home + work charging scenario.

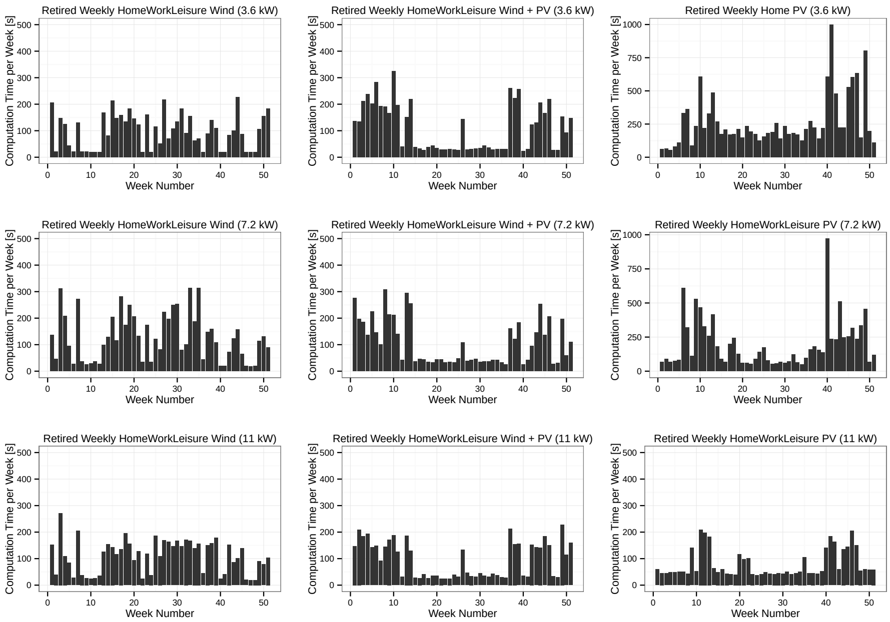


Figure G.11: Computation times overview for the optimal benchmark case for retirees in the weekly optimization home + work + leisure charging scenario.

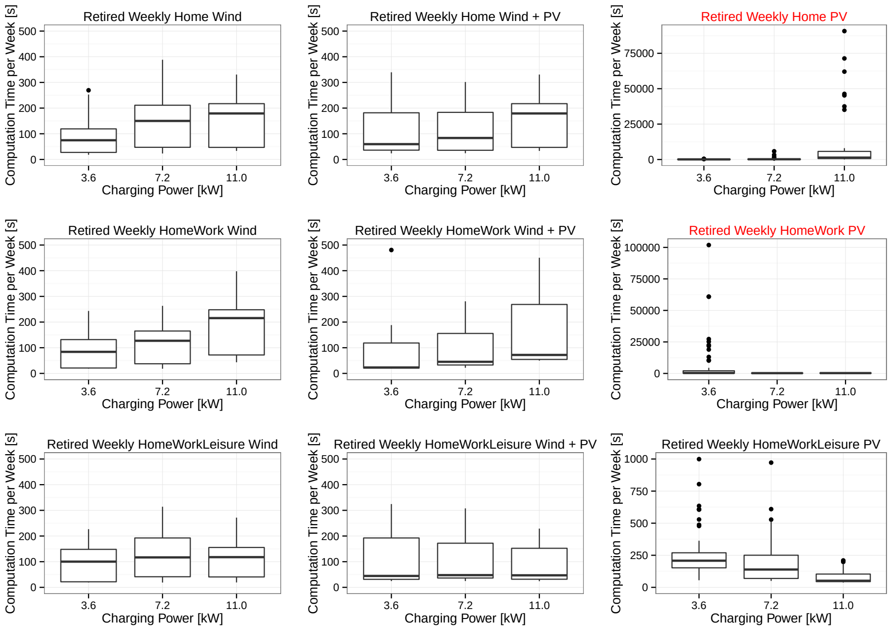


Figure G.12: Variation of computation times for the optimal benchmark case for retirees in the weekly optimization scenario.

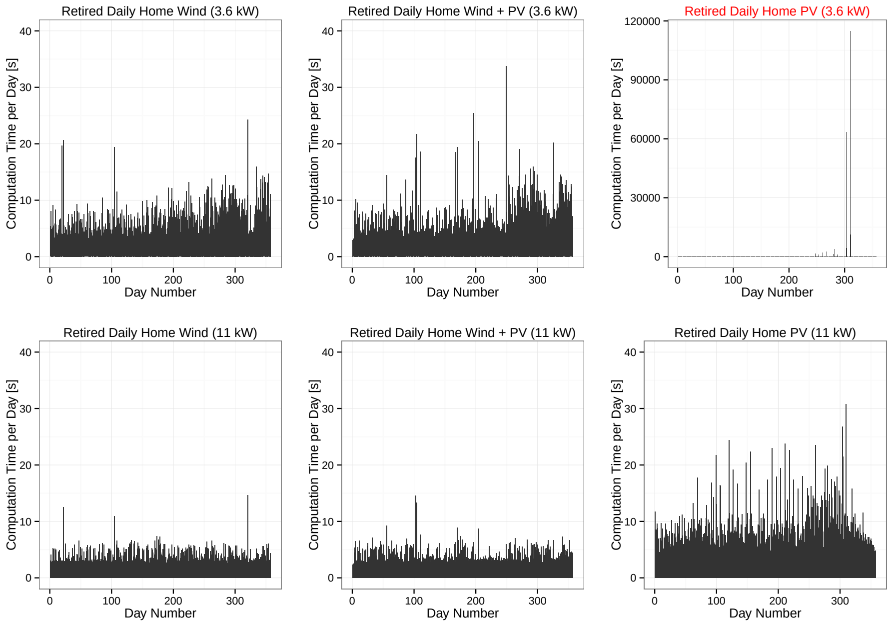


Figure G.13: Computation times overview for the optimal benchmark case for retirees in the daily optimization home charging scenario.

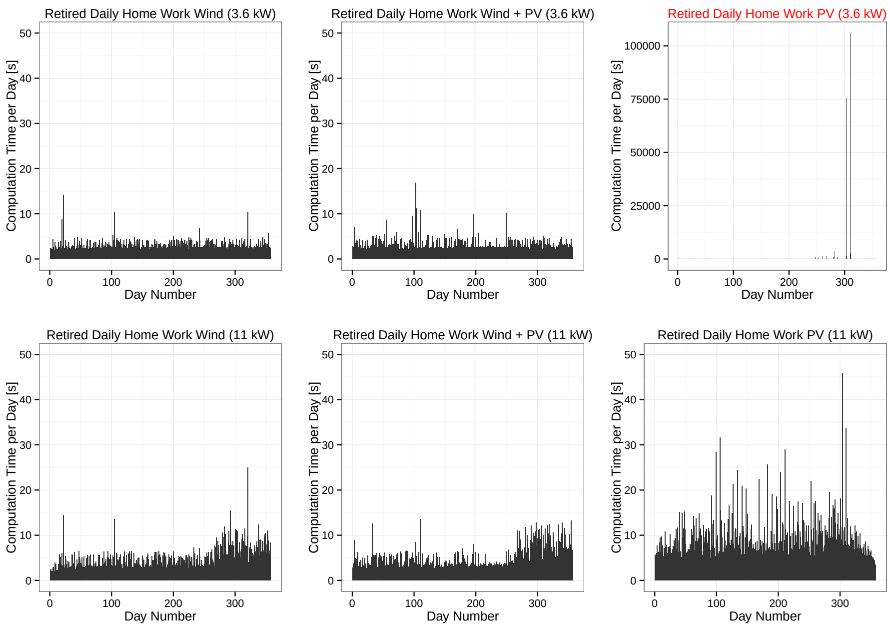


Figure G.14: Computation times overview for the optimal benchmark case for retirees in the daily optimization home + work charging scenario.

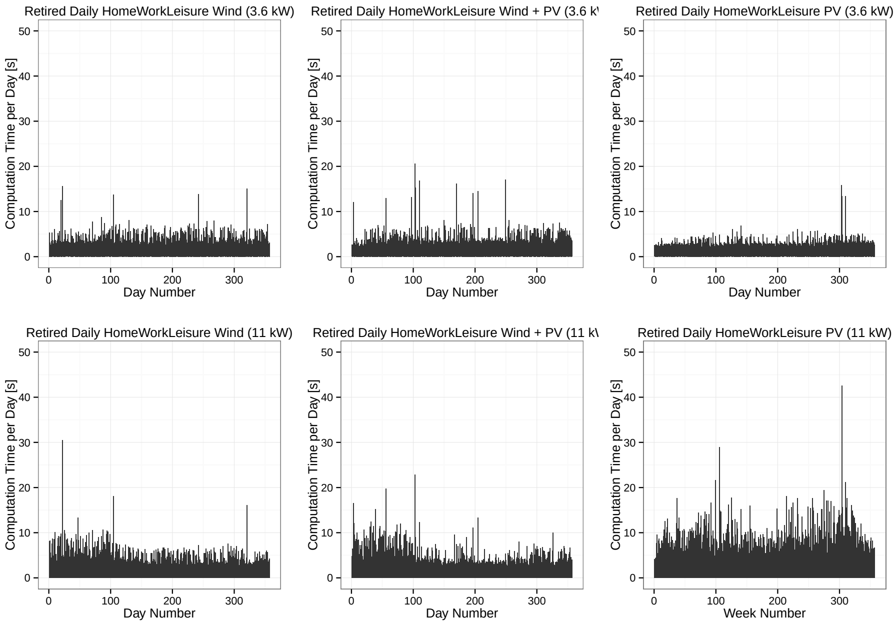


Figure G.15: Computation times overview for the optimal benchmark case for retirees in the daily optimization home + work + leisure charging scenario.

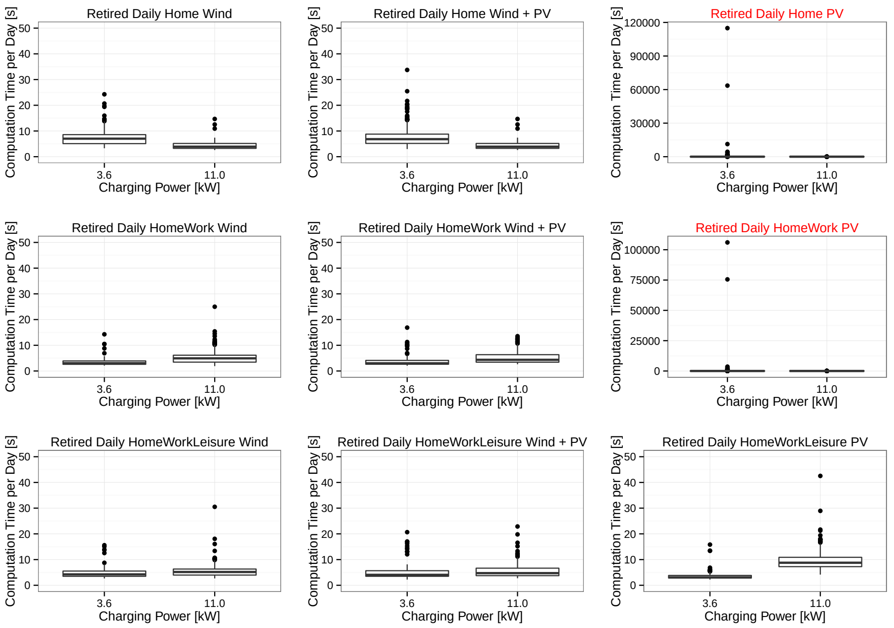


Figure G.16: Variation of computation times for the optimal benchmark case for retirees in the daily optimization scenario.

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