The Power of Electric Vehicles

Exploring the value of flexible electricity demand in a multi-actor context

R.A. Verzijlbergh

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Remco Verzijlbergh,
Delft, September 2013.

Chapter 1

Introduction

1.1 The changing energy landscape

1.1.1 The growth of renewables and its drivers

Realizing a transformation to a sustainable energy based economy is one of the great challenges of our time, because it addresses one of the biggest threats to life on earth as we know it: anthropogenic global warming. The International Panel on Climate Change (IPCC) reports are the remarkable materialization of many years of climate science, and they leave little room for doubt: in order to maintain a livable planet, carbon emissions should drastically be reduced [1][1]. This calls for fundamental changes in our society, and most notably in our energy system. A quote from Nobel-prize winning chemist Sherwood Rowland related to the ozone debate can be considered appropriate in the discussion on climate science, global warming and renewable energy policy, too:

'What is the use of having developed a science well enough to make predictions if, in the end, all we are willing to do is stand around and wait for them to come true?'

However, despite the overwhelming scientific evidence for anthropogenic global warming, a number of skeptical voices are still being heard. In the end, their argument often has an economic character: the costs of preventing an uncertain global warming scenario to happen are simply too high. Nevertheless, next to the environmental arguments, economic and geopolitical considerations are equally important drivers towards a departure from a fossil fuel based economy. In the longer run, prices of finite natural resources will inevitably rise as the most easily accessible resources will become depleted. When zooming in on shorter timescales, one observes developments that can temporarily alter long term trends, such as financial crises or technological breakthroughs like the new shale gas production techniques in the

[1] In September 2013 a draft version of the 5th IPCC report was published. The officially approved version is expected in January 2014. The approved executive summary of the draft version shows roughly the same conclusions as the 4th IPCC report.

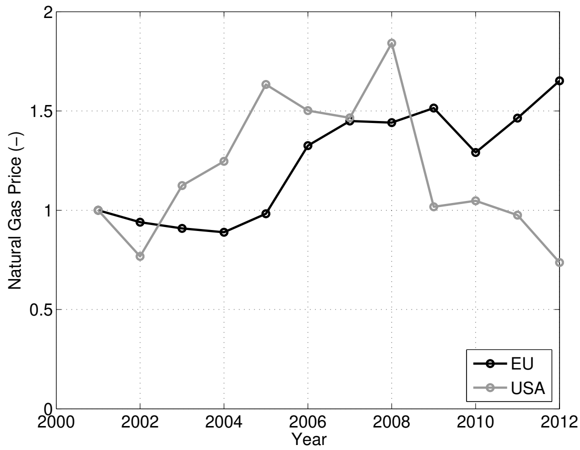


Figure 1.1 – Normalized (with respect to 2001 levels) natural gas price development for large industrial consumers in the US and Europe. Data from [2] and [3].

US. As an illustration, Fig. 1.1 shows the recent trends in natural gas prices for industrial consumers, relative to the levels of 2001. One observes how in Europe the trend is clearly upwards, with a little dip that marks the 2010 post-crisis dip in oil prices. On the other hand, after 2008, the massive deployment of shale-gas extraction technology has seriously lowered US gas prices. This pictures also reveals a slight fraction of the complex geopolitical issues that play a role around energy. While the US have increasingly become an independent producer with a domestic production that meets a large portion of demand, Europe has become more dependent on other countries. Two opposite trends in gas prices are the result.

The largest economic driver towards renewable energy sources (RES) are, however, not so much the rising costs of fossil fuels, but the spectacularly decreasing costs of RES themselves. In particular the cost of solar photo-voltaic (PV) energy has dropped dramatically in recent years. Both wind and solar PV now have similar levelized costs per MWh as most conventional generation technologies. This point is illustrated clearly in Fig. 1.2, that displays the total levelized costs of different generation technologies. One observes 1) the enormous reduction in solar PV costs in only three years time and 2) the fact that wind energy has already the third lowest cost, after the modern gas turbines, whose costs have mainly dropped because of the shale-gas revolution. Looking at these figures, one can state that it is possible or even likely that RES will soon simply become the cheapest way of generating electricity.

Because of the environmental, economic and geopolitical concerns outlined above, governments around the world are taking action and ambitious decarbonization targets have been formulated. For example, the EU has a long term goal of 80-95% reduction of greenhouse gas emission in the power sector by 2050 [4]. The recently presented energy plan from the Obama administration wants to double the share of RES by 2020 [5]. In the Netherlands, a recent 'national energy agreement' outlines

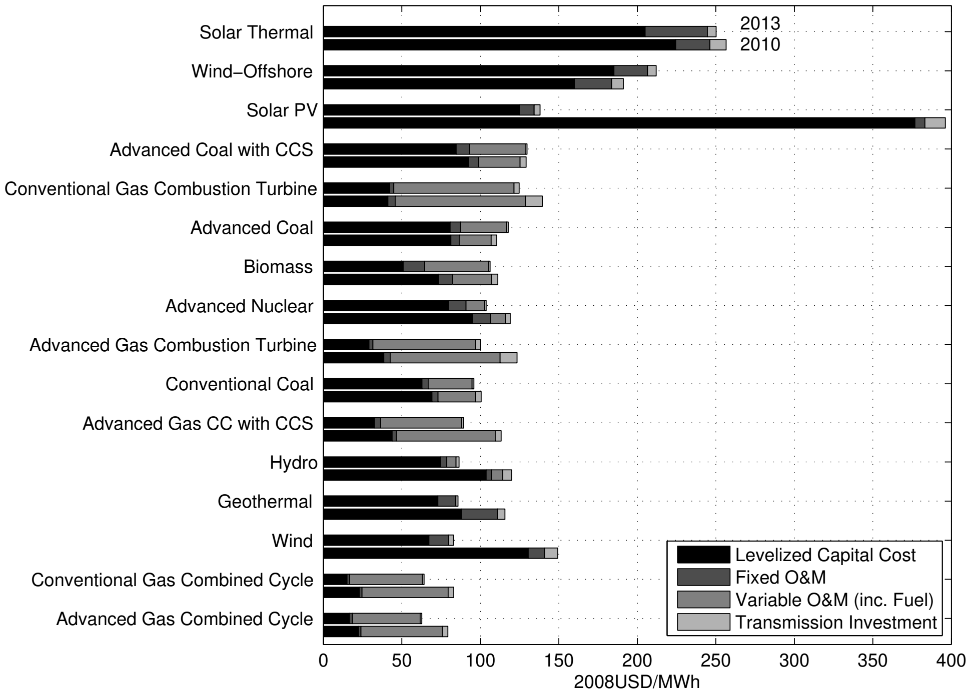
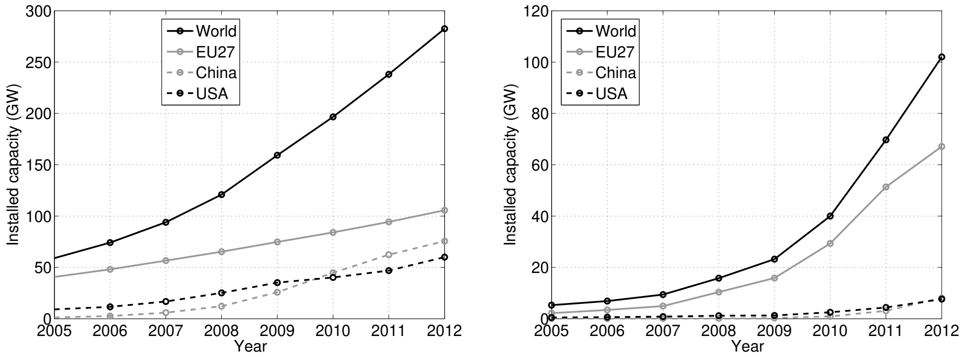


Figure 1.2 – Comparison of generation cost estimates from 2010 (lower bars) and 2013 (upper bars). Numbers denote USA average levelized costs (2008 \$/MWh) for plants entering service in 2016 (for the 2010 numbers) and 2018 (2013). Generation types are ranked according to the 2013 costs. Data from [3].



(a) Cumulative installed wind power

(b) Cumulative installed PV power

Figure 1.3 – Cumulative installed capacities from 2005 to 2012 of wind power (a) and PV power (b). Data from [9], [10] and [11].

strategies for a fully sustainable energy system in 2050.[2]

In some countries, RES policies have already led to a sharp increase in the installed capacities of clean generation technologies. Fig. 1.3 shows the installed capacities of wind and PV power worldwide and in some key regions. The installed wind generation capacity in 2012 was more than 5 times the one in 2005; for solar the installed capacity in 2012 was more than 10 times the capacity in 2005. While Europe contributed to most of the observed growth in the earlier years of the 2005-2012 period, other countries are catching up rapidly. Most projections show continuing strong growth of both wind and solar, see e.g. [7], [8] and [9].

The fast and inevitably growing shares of RES have a profound effect on the functioning of power systems. Traditionally, the stable and secure operation of power systems relies on forecasting electricity demand and scheduling the necessary power generation in the most economic way, taking into account appropriate reliability margins and technical constraints. The typical characteristics of wind and solar power introduce a number of complexities to this model. The chaotic and intermittent nature of atmospheric processes is the main source of these complexities: not only is the output of wind and solar power plants very variable by nature, it is also hard to predict. These two characteristics, variability and uncertainty, pose a number of challenges to the planning and operation of power systems, see e.g. [12]. In this report, among many others, it is argued that *flexibility*[3] is key in dealing with the variability and uncertainty of wind and solar generation. Four sources of flexibility are identified: flexible generation, storage, interconnection and demand response. For the latter to play a serious role, a large source of flexible electricity demand is required, but today this source is virtually non-existent, since electricity demand has proved to be almost completely inelastic. This premise may well change

[2]The short-term targets are, however, not nearly as ambitious: 16% renewable energy by 2023, which is a lower target for a later moment than previously stated goals [6].

[3]In [12] flexibility is defined to *"express the extent to which a power system can modify electricity production or consumption in response to variability, expected or otherwise"*

in the coming years.

1.1.2 The advent of electric vehicles

Roughly the same concerns that push RES can also be considered to drive the introduction of electric vehicles (EVs)[4]: rising oil prices, a large dependency on a small number of oil producing countries and greenhouse gas emissions caused by road transport. Reductions of tail-pipe emissions form another important advantage of EVs because they can significantly reduce local air pollution problems.

Governments worldwide are acknowledging the potential of EVs and are therefore formulating ambitious EV penetration targets [13]. Various measures to promote their introduction are proposed, some of which are already being implemented in various countries. They include tax benefits, research programs, but also initial investments in charging infrastructure. Two milestones that are mentioned are a worldwide 50% market share in 2050 and at least 5 million EVs and PHEVs sold per year as of 2020. In [13] it is also argued that the path to a large-scale EV introduction is not without obstacles. Most notably, improved battery performance and reduced battery costs are necessary for EVs to successfully compete with conventional vehicles and achieve the large market shares that are so ambitiously formulated. Estimates on the pace of the introduction of EVs and total market volumes therefore vary markedly and are subject to many uncertainties regarding raw material reserves, oil prices, stimulating policy instruments, technological breakthroughs, etc.

As an illustration, Fig. 1.4 shows the EV penetration scenario as envisioned by the Dutch government in 2009 [14]. In this scenario, the market eventually saturates at 75% of all passenger vehicles. Although the significance of such predictions in the early stages is questionable, it is interesting to remark that in the first few years the actual observed number of registered EVs is higher than this government forecast from 2009. As of July 2013 there are already more than 10.000 electric vehicles on the road in the Netherlands [15].

1.1.3 The potential synergy between electric vehicles and renewable energy sources

The two trends described above, the large scale adoption of RES and EVs, have some interesting potential synergies. The key to this potential lies in the potential flexibility in the charging process of EVs, i.e. to vary charging power and/or postpone charging. For example, for a typical EV and average driving behavior, an EV owner needs to re-charge his car every four days. This flexibility can play a crucial role in power systems with a large RES penetration, since it could replace the flexibility that is normally provided by conventional generation units but that most RES are only able to provide to a limited extent. Instead, flexible electricity demand can be adjusted according to the availability of RES output. The contours of this paradigm shift begin to appear: from a fixed demand that is met by controlling the generation

[4]In this thesis we will not differentiate between plug-in hybrid electric vehicles (PHEVs) and full electric vehicles and we will denote all with the acronym EV

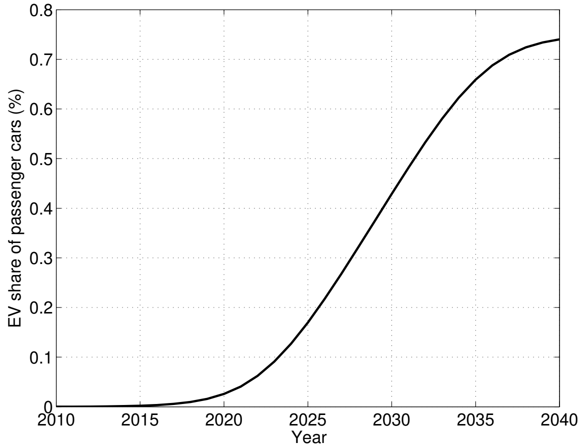


Figure 1.4 – EV penetration scenario forecasted by Dutch government [14].

side, towards a controllable demand side that follows the fixed but time varying generation. Although a complete reversal of the traditional paradigm is not likely, i.e. flexible generators will always be needed to some extent, responsive demand is expected to play a major role in high RES power systems [16].

1.1.4 Changing roles in future power systems

The more active role of electricity demand could well lead to a re-definition of traditional rules and roles in power systems. With the introduction of distributed generation and demand response, the demand side of the sector will become more actively involved. For instance, new types of services based on the flexibility in demand and/or distributed generation could emerge. Any of these services will need to be accommodated by the electricity networks, and some services might even be specifically aimed at the network. The new market models can only be created in a meaningful way if the techno-economic characteristics of the new paradigm are thoroughly understood. This thesis aims to contribute to this understanding by analyzing the potential of flexible EV demand in the multi-actor context of liberalized power systems with high shares of RES.

1.2 This thesis

1.2.1 Problem description

In liberalized power systems, different tasks regarding the planning and operation of the power system concern different actors. The flexibility of EV charging therefore also contains a value for a variety of actors. Distribution system operators (DSOs), for example, have an interest in controlling the EV charging process in such a way that sharp peaks in network load are avoided, since they could require reinforcements of networks. On the other hand, retailers who buy electricity on wholesale markets could benefit from lower off-peak wholesale prices if they can postpone EV charging to low price periods. Yet another perspective is if EV charging power is being adjusted with regard to the variable output of renewable energy sources.

1.2.2 Research objectives

The question thus arises how EV charging flexibility can add the most value, and, consequently, how this flexibility can best be 'shared' among different actors. The research objective of this thesis can be therefore be formulated as *gaining a better understanding of the potential value of controlled EV charging in liberalized multi-actor power systems with high shares of renewable energy.*

This objective motivates the following research question:

How can the flexibility of EV charging best be utilized in multi-actor power systems with high shares of renewable energy sources?

In order to answer the main research question, a number of subquestions have been formulated.

1. How can the controlled charging of EVs reduce their impacts on the distribution grid?
2. How can controlled EV charging reduce generation costs in power systems with a high share of renewable energy sources?
3. How can the costs of EV charging be minimized within distribution grid constraints?

1.2.3 Thesis outline, structure, research methods and scope

This thesis addresses the questions formulated above in the following structure: chapter 2 provides the necessary background knowledge of the system under consideration. It treats the relevant technical and economic aspects of power systems and describes relevant characteristics of EV charging. In chapter 3 we present a literature analysis to identify knowledge gaps and position the work described in this thesis relative to the literature.

Chapter 4 treats the first sub-question listed above. It first assesses the impacts on the distribution grid caused by EV charging and then analyzes the potential cost savings of controlled EV charging due to lower network investments and energy losses. The networks analyzed in this chapter cover a large part of the complete Dutch distribution network, and the time-horizon extends to 2040.

Chapter 5, which deals with the second sub-question, looks at the flexibility of EV charging from the perspective of electricity generation in system with a high share of RES. By extending a unit-commitment model with EV charging as optimization variable, the flexibility of EV demand with respect to variable RES output is analyzed in combination with cross-border transmission capacity. The system analyzed in this model is based on projections for the German power system in 2025.

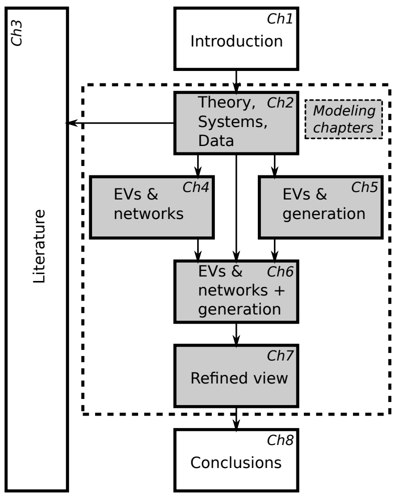


Figure 1.5 – Schematic representation of the thesis structure and chapter numbers.

The final sub-question is treated in chapter 6. Here, the effect of EV charging based on wholesale electricity prices on the distribution network is analyzed for an example distribution network. Moreover, possible mechanisms to prevent EV charging from overloading the networks are discussed.

Chapter 7 treats a number of additional aspects of EV charging and aims to connect the different viewpoints of the earlier chapters. Most notably, we investigate the differences between a centralized and a decentralized approach to EV charging. Furthermore, a sensitivity analysis on various assumptions made in earlier chapters, as well as an analysis of the effect of cost-minimizing EVs on the same set of networks that was used in chapter 4 are presented. The thesis ends with conclusions, reflection and recommendations.

The thesis structure is summarized schematically in Fig. 1.5. Chapters 4, 5 and 6 have been published or submitted as journal papers and we have chosen to include them integrally in this thesis. As a consequence, these chapters themselves start with introductory texts which will inevitably contain some repetitions compared with earlier chapters.

Different research methods and data have been used in the work presented in this thesis and they will be explained in more detail in subsequent chapters. In short, we have mainly used mathematical optimization models combined with EV data that has been derived from current driving patterns from conventional vehicles users. We assume rational, cost-minimizing entities and, throughout the thesis, we model all optimization problems as deterministic, so we do not take various types of uncertainties into account. Some further limitations of scope are the following:

- We do not consider EV charging optimization for the provision of balancing services. Although this clearly is a promising venue for flexible EV demand, we choose not to include it in this thesis for a number of reasons. One of the important reasons are that there already exists a large body of scientific literature on this topic, which is discussed in further detail in chapter 3. Secondly, a meaningful analysis of the potential value of EVs with respect to balancing services requires stochastic optimization methods combined with realistic data of forecast uncertainties, which were not readily available.

- The penetration rate of EVs and/or RES is taken as given. We do not consider strategies to promote the adoption of EVs, renewable energy policies, etc.
- The IT infrastructure needed to control EVs, communicate price signals, etc, is largely out of scope of this thesis. In chapter 6 we briefly comment on the IT requirements of different congestion management schemes for distribution grids. Issues like robustness, safety and topology of EV related IT infrastructures are not treated.
- Consumer behavior with respect to EV charging is based solely on driving patterns. We do not focus on what incentives are most effective for consumers to provide demand response services.
- Vehicle-to-grid, or V2G, where EVs can feed electricity into the grid is not considered in the main text of this thesis, except for appendix A.
- In the optimization formulations of chapters 5, 6 and 7 we look at minimizing short term variable costs, so investment in new assets as decision variables, either in generation or network capacity, are not considered.

The work described in this thesis was performed at the section Energy and Industry of the department of Technology, Policy and Management at Delft University of Technology. Its signature can be recognized in this work, since multi-actor infrastructure systems lie at the very heart of this group. Parts of this research have been performed in close cooperation with Dutch DSO Enexis.

Chapter 2

Electric vehicles in future power systems

In this chapter we aim to provide some elementary background that is considered helpful for a better understanding of the remainder of this thesis. To this end, we start with a brief review of the technical and non-technical aspects of today's power systems[1] and we will especially emphasize ongoing trends and expected changes. Then we focus on the role of EVs by discussing relevant actors concerned with EV charging, presenting a model for EV charging based on a dataset of current driving patterns, and showing how various EV charging strategies can be formulated as mathematical optimization problems. This will constitute the modelling framework used throughout this dissertation.

Regarding the first section of this chapter that gives some background on power systems, we note that this is only a very concise overview with a limited scope fitting the issues treated in this thesis. As a consequence, many important aspects are not discussed here and we refer the reader to a number of textbooks on technical and non-technical details of power systems, such as [16], [17], [18], [19], [20] and [21].

2.1 Power systems

2.1.1 Technical aspects

Traditional functioning The main technical functions of a power system are generation, transmission, distribution and consumption. Current power systems are characterized by a hierarchical top-down structure, as depicted schematically in Fig. 2.1.

Power is generated mostly by large power plants, where it is immediately transformed to higher voltages and fed into the transmission network. The main function of the transmission network, usually a meshed network to ensure redundancy, is

[1] When we refer to power system we actually mean the *electric* power system.

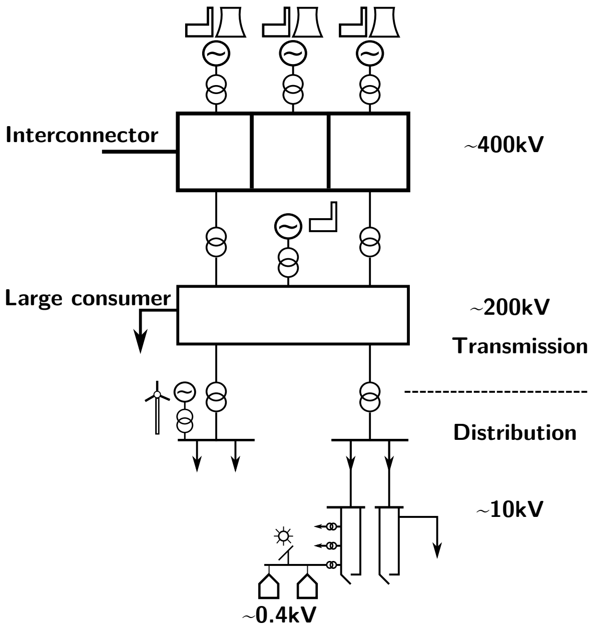


Figure 2.1 – Schematic view of the structure of current power systems.

to transport power at a high voltage from the generation sites towards load centers. Typically, voltages range between 150 kV and 400 kV, but in some countries higher voltages are common as well. Interconnectors - transmission lines to neighboring countries and/or power systems - are found both in alternating current (AC) and direct current (DC) form, the latter being used mainly for longer distances or to connect non-synchronous regions. The boundary between the transmission grid and the distribution grid lies at the high voltage (HV) substations, where voltage is transformed down to lower levels. From the HV substations a number of MV-transmission (MV-T) cables (typically 10 kV or 20 kV) transport power further to MV substations, where a number of MV distribution (MV-D) cables are fed. MV-D cables are often laid out in a ring structure, with a net opening that is open under normal operation. In case of a fault on the MV-D cable, the net opening closes automatically such that no interruption of supply is experienced by the loads connected to the MV-D cable. Connected to the MV-D cables are MV/LV transformers, that typically serve 50-100 households through a number of LV feeder cables. Household electricity consumption hence takes place at the lowest voltage level, but medium sized and large industrial customers can be connected to higher voltage levels, up to the high voltage transmission grid for very large consumers. Furthermore, a limited amount[2] of distributed generation is connected to the distribution grid, either at medium voltage (e.g. medium sized wind turbines, combined heat and power (CHP) installations) or at low voltage (PV panels, micro CHP). It should be noted that many variations of the typical topography described above exists between countries,

[2]This is true for most countries. Germany with its 35 GW of solar capacity forms an exception.

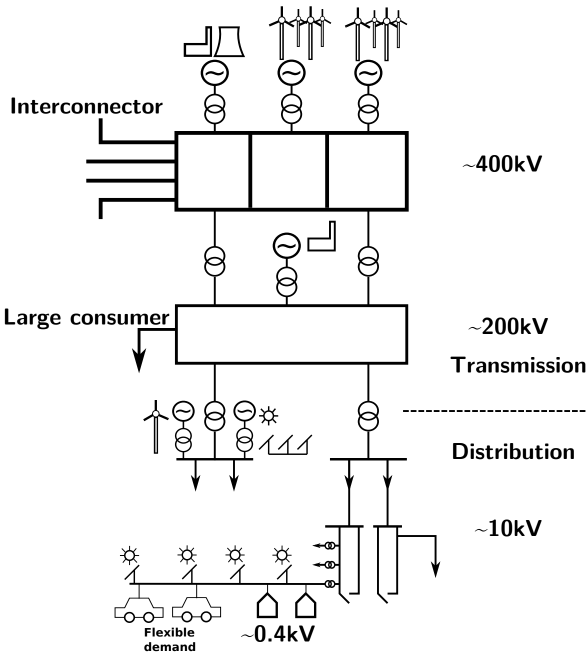
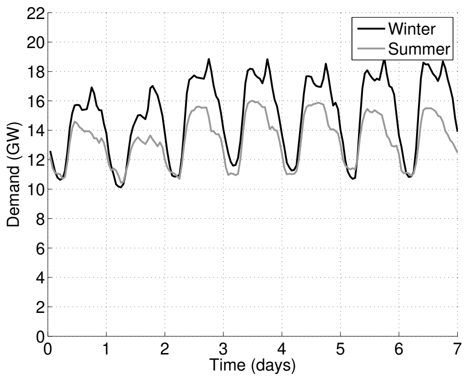


Figure 2.2 – Schematic view of the structure of future power systems with increased RES penetration, interconnection capacity and flexible demand.

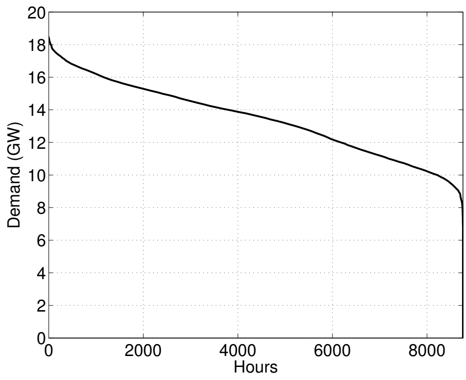
and even within countries and regions. For example, on the MV-level one finds many combinations of ring, meshed and radial configurations.

Trends towards future power systems A number of changes that are taking place in power systems across the globe can be identified, depicted schematically in Fig. 2.2. Presumably the most profound one is the sharp increase in RES, as Fig. 1.3 clearly demonstrates. The two main renewable generation technologies are wind power and, more recently, solar PV power. While the former is mostly embedded at medium, and increasingly so, at high voltage levels, the latter is predominantly connected to the grid at LV level. The variable, unpredictable and non-dispatchable nature of RES makes them hard to integrate. Additional electro-technical complexities such as a lower system inertia provided by rotating mass and voltage stability play a role as well.

Partly as a reaction on and anticipating growing RES penetration levels, a number of other changes are taking place. One observes an increased level of interconnection between countries, both AC and DC, and ENTSO-E scenarios [8] show that this trend is likely to continue. Interconnectors, traditionally used mostly for reliability reasons, now increasingly facilitate the coupling of electricity markets. In the light of high RES levels this becomes particularly interesting due to the geographic smoothing effect: the RES output over a larger geographic area shows a more constant production profile. Furthermore, pumped hydro resources in neighboring countries can act as buffers for RES production - the case of Denmark and



(a) Load profiles



(b) Load duration curve

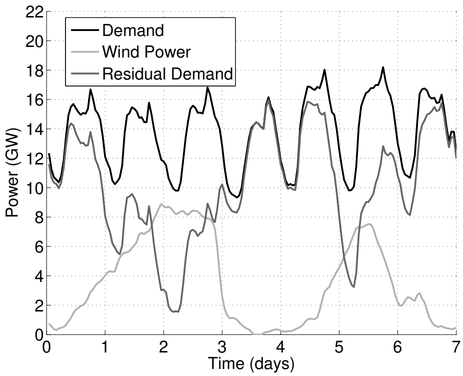
Figure 2.3 – Demand profiles in a summer and winter week (a) and load duration curve (b) in the Netherlands in 2012.

Norway is exemplary. As RES levels are increasing and power systems are merging, an important role is also foreseen for FACTS technology (Flexible AC Transmission System). FACTS provide a means to, to some extent, control flows in the transmission grid, thereby enabling a more efficient operation of the grid.

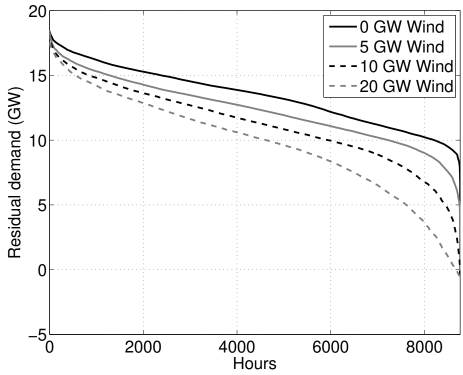
On the demand side, the electrification of transport and domestic heating are leading to the introduction of new loads that have a more flexible character than traditional household loads: electric vehicles and heat pumps. In addition to this, micro CHP creates another source of flexibility embedded at household level. Together with developments in IT that enable an infrastructure for communication and control, the new flexible electricity demand can become an important part of the electricity system, that partially takes over functions that are traditionally supplied by the large conventional generation units.

2.1.2 Load and generation profiles

System load, renewable energy and residual demand Electricity demand typically varies with time depending on the season, day of the week and hour of the day, but also on prevailing weather conditions. In moderate climates the system peak usually occurs on a winter evening, while in warmer climates the use of air conditioning causes demand peaks in warm summer afternoons. Fig. 2.3(a) shows the system demand in the Netherlands in a typical winter week and a typical summer week. Information on the yearly load profile is often expressed in a load duration curve, that basically ranks the hourly demand in descending order and can be interpreted as a probability distribution. Fig. 2.3(b) shows the load duration curve for the Netherlands in 2012. The minimum load lies around 8 GW whereas the maximum is a little under 18 GW. The load duration curve also shows at a glance how many hours the system demand is larger than a certain value. This information is important since it determines what mix of power plants can meet the time varying



(a) Residual load profile



(b) Residual load duration curve

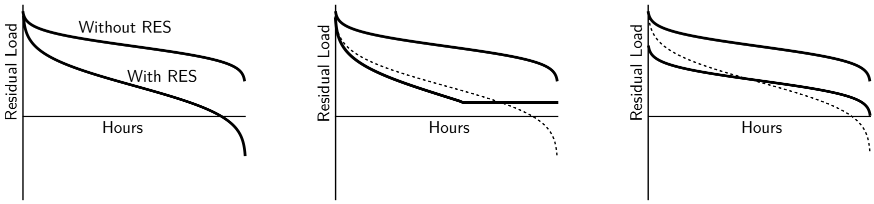
Figure 2.4 – Modeled residual demand profile in a winter week (a) and modeled residual load duration curves for different wind capacities (b) in the Netherlands in 2012. A negative residual demand denotes a surplus of wind generation.

yearly demand in the most economic way. Coal plants, for example, have relatively high investment cost and low variable costs and are cheaper than gas plants when they can run for more than, say, 6000 hours per year.

A concept often used in relation with RES is the residual demand, which is defined as the demand minus RES production. This is the demand curve that has to be met by dispatchable generators. As the share of RES grows, it has a large impact on the residual demand curve. Fig. 2.4(a) shows the same winter week as Fig. 2.3(a), but this time also wind production scaled to 10GW installed wind capacity and the resulting residual demand have been plotted[3]. It can be seen that since wind power is variable, and in principle uncorrelated with demand, a residual load curve emerges that still shows some daily pattern, but also the randomness induced by the variable wind power. Naturally, the higher the installed capacity of wind power, the stronger this effect is. For solar power a similar effect can be expected, although, due to the daily cycle of the sun, solar power is more correlated with demand than wind power.

The residual load duration curves shown in Fig. 2.4(b) demonstrate the effect of more RES in another way. One notes that especially the amount of base-load hours (in the right of the figure) decreases quickly when more wind power is installed. The peak demand does hardly decrease however. This is due to the fact that, since wind power and demand are uncorrelated, there will always be some hours with high loads and low wind. By looking at Fig. 2.4(b) one is able to understand the potential value of demand response and interconnection capacity. The former effectively shifts demand from low residual demand periods to high residual demand periods, which would result in a flattening of the residual load duration curve. Interconnection, on

[3]Since aggregated wind power time series for the Netherlands are not available, the wind power time series are based on data from the western Danish system that has similar wind characteristics as the Netherlands.



(a) Residual load curves with and without RES.

(b) Effect of demand response on residual load duration curve.

(c) Effect of interconnection on residual load duration curve.

Figure 2.5 – Residual load duration curves and the (exaggerated) effect of demand response (b) and a smoother RES profile due to more interconnection (c). The dashed line in (b) and (c) denotes the residual load duration curve with RES from (a)

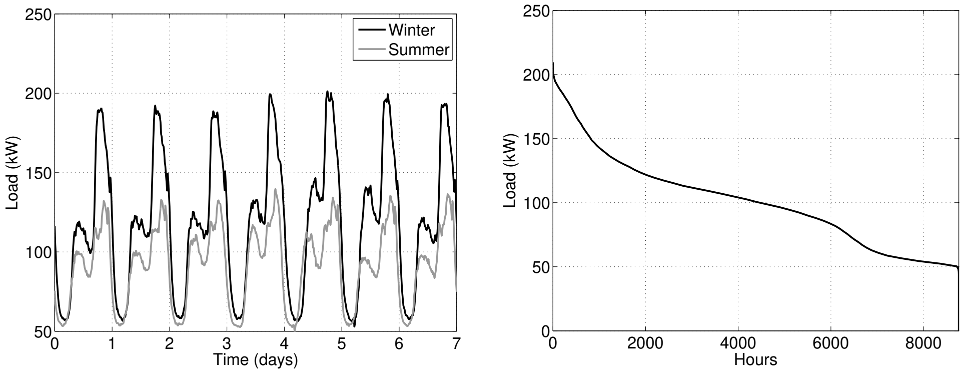
the other hand, leads to a more constant aggregated RES production profile, so that the residual load duration curves looks more like a shifted version of the original load duration curve depicted in Fig. 2.3(b). Fig. 2.5 shows these effects in a schematic and exaggerated way.

Load profiles in distribution networks and energy losses The total system load profile that was shown in Fig. 2.3 represents the sum of all electricity demand in the Netherlands. On lower levels of the network, a differently shaped profile is observed, due to the fact that the large consumers with flatter load profiles are connected at the higher voltage levels. The exact combination of loads connected to a certain distribution assets determines the load profile (i.e. the power flow as a function of time) on that asset. Typical load profiles for a winter week and a summer week on a LV/MV transformer with approximately 250 households connected to it are depicted in Fig. 2.6(a). The yearly load duration curve is shown in 2.6(b). Compared with the national system load profile depicted in Fig. 2.3 the household load profile shows much more variation between peak demand and low demand.

Due to the random nature of loads, the combined peak of many loads $P_i(t)$ is usually much smaller than the sum of the individual peaks. The ratio of these two is defined as simultaneity factor g (sometimes its reciprocal diversity factor is used):

$$g = \frac{\max \sum_{i=1}^{N} P_i}{\sum_{i=1}^{N} \max P_i} \tag{2.1}$$

The value of g depends on the network level and is usually smallest at the lower levels. Working formulas exist for relations between consumed yearly energy of loads (this is typically what is measured by DSOs) and the expected combined peak of those loads. Such formulas are being used by network planners if new networks have to be constructed. If, for example, a new residential area is being built, one estimates expected electrical energy use based on the type of housing and dimensions the networks to be able to supply expected peak loads. Naturally, higher capacity assets are more expensive.



(a) Load profile

(b) Load duration curve

Figure 2.6 – Standard household load profile of 250 households in a summer and winter week (a) and the load duration curve (b). Data from [22].

Next to the capital costs of assets, a second large cost associated with the distribution networks are energy losses. Energy losses in a conductor, say a line l are given by Ohm's law:

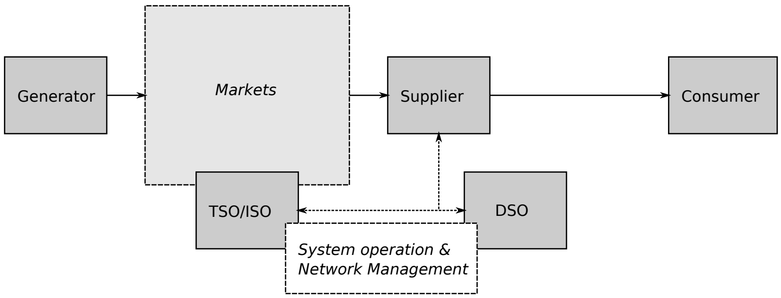
$$P_{loss,l}(t) = I_l^2(t)R_l \tag{2.2}$$

where I_l is the current in the conductor and R_l its resistance. If ones assumes a constant voltage, the energy losses scale with $P_l^2(t)$ where $P_l(t)$ is the instantaneous power in the line. The ratio between energy and peak load is called *service time* and is a measure for the 'flatness' of the load profile. A flat load profile (higher service time) hence leads to lower energy losses. Furthermore, the service time is a useful measure to estimate yearly energy losses based on only a measurement of the yearly peak load.

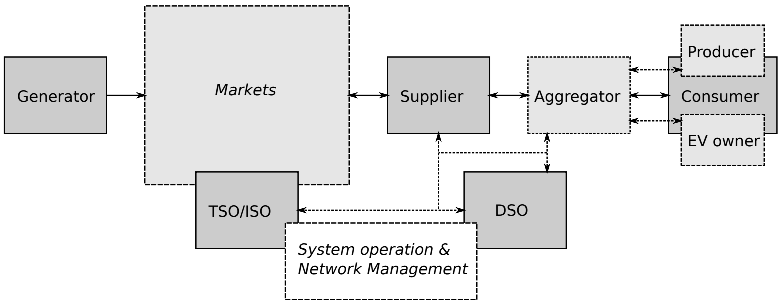
2.1.3 Non-technical aspects: organizational, economical, and regulatory

Liberalization and unbundling: a multi-actor system Many power systems around the world have undergone a transition from being centrally operated to allowing for competition in the generation and retail of electricity. This process, often referred to as restructuring or liberalization, has also led to the unbundling of generation and transport of electricity in many countries. In addition, transport of electricity is often divided in a transmission and a distribution network, where transmission networks are operated by one or a few transmission system operators (TSOs) and distribution grids by distribution system operators (DSOs). A number of textbooks describe liberalized (also referred to as restructured) power systems in much more detail, see e.g. [16, 18, 19, 20].

The resulting structure of the electricity sector can hence be described as a multi-actor system with different actors operating in different technical areas of the system. Naturally, different actors also have different objectives that are specific



(a) Actor overview current situation



(b) Possible actor overview future situation

Figure 2.7 – Schematic representation of actors in the current electricity sector (a) and a possible representation of the future situation with small producers and flexible demand (b). Arrows denote contractual relationships and flows of information. Figures based on [23].

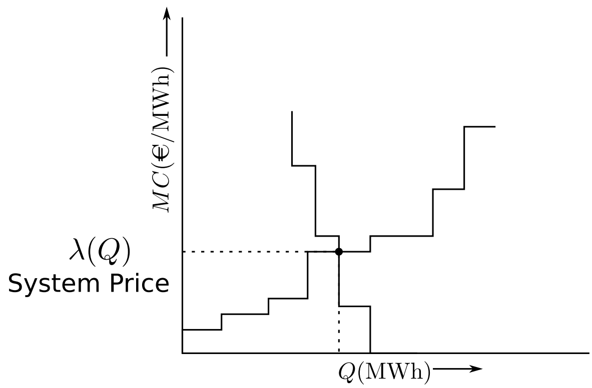
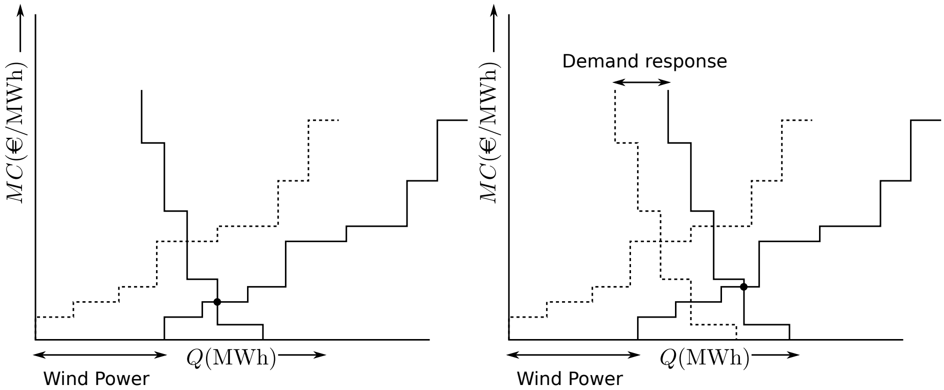


Figure 2.8 – Schematic representation of electricity price setting by the marginal unit. MC denote marginal costs of generation units and Q the demand of electricity.

for their tasks. Fig. 2.7(a) provides a schematic overview of the actors operating in todays unbundled power systems.

With the changes described in the previous section - the advent of multi-national markets, more RES and increased volumes of distributed generation and flexible demand - the traditional roles in the electricity sector are changing, too. As an example, one could think of the market for balancing services. Currently, generators offer bids for balancing power and are dispatched according to the system imbalance, and, to some extent, large consumers that have a suitable consumption profile might offer balancing power in the form of interruptible load contracts. In the future, small consumers with flexible demand and/or distributed generation, possibly represented by some aggregating entity, might begin offering those services as well. Also, functions related to the networks like congestion management on the transmission grid, or energy balancing on the distribution network level (currently not taking place), could be expected to be fulfilled by demand response and distributed generation in a cost-effective way. In a nutshell, one might say that if the controllable conventional generation will be replaced by less flexible RES and, simultaneously, more flexibility on the demand side, it is a logical consequence that a part of the services provided traditionally by the conventional power plants will now be transferred to the demand side. Fig. 2.7(b) provides a possible schematic overview of the actors in such a future power system.

Supply and demand, electricity price, economic dispatch One of the fundamental results of the theoretical underpinning of power systems restructuring is that centralized dispatch of electricity generation leads to the same outcome as in a perfectly operating electricity market, which is that all generating units in the system will increase their output until the point their marginal cost is equal to the system marginal cost which is sometimes called ‘system lambda’. The derivation of this result can be found in standard textbooks, e.g. [17] and [20]. The implication of this result is that the optimal electricity price will reflect the marginal cost of the marginal unit in the system, i.e. the most expensive (in terms of marginal cost)



(a) Merit order wind power

(b) Merit order with wind power and demand response

Figure 2.9 – Schematic view of how electricity price changes due to wind power and demand response. In the left figure the dashed line represents the original merit order without wind, in the right the second dashed line represents the original demand curve without demand response.

power plant that is needed to meet the demand. In a market this price is the result of supply bids by the generators - economic theory suggests that the optimal bids are exactly at marginal cost. Fig. 2.8 shows schematically how the electricity price emerges from demand and supply bids and reflects the marginal cost of the marginal generator.

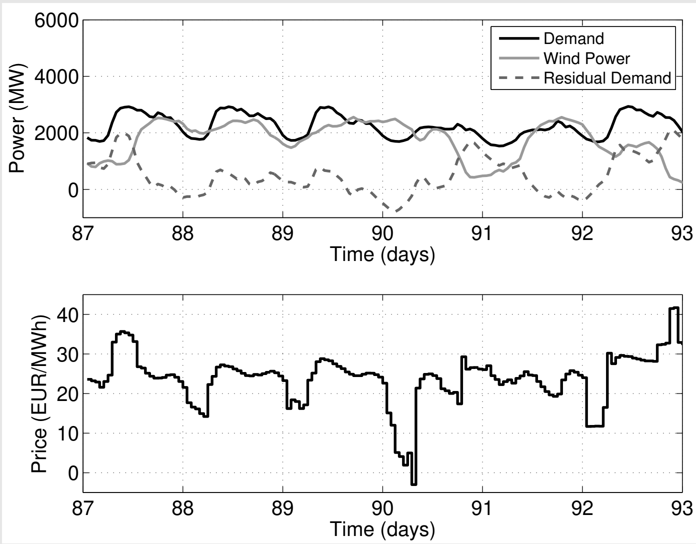
In reality, next to the marginal cost of generators, there is a number of other factors that are of importance for how electricity prices emerge. Most notably the so-called inter-temporal constraints play a role. These express, loosely speaking, constraints on generators' output between different time-steps. In other words, if a generator is now producing at a certain operating point, this restricts the possible operating points in future time-steps. Examples of such constraints are that units have a start-up times (and/or costs) and ramping limits, i.e. they cannot adjust their output infinitely fast. In a market environment, a large variety of other issues plays a role.

With the ongoing changes in the electricity sector, mostly the much higher RES penetration, electricity price formation will be influenced, too. In principle, RES have a marginal cost of zero, or, when taking non-fuel related variable operational and maintenance cost into account, very close to zero. If renewable energy is, like conventionally generated electricity, traded on the spot market, the merit order will hence start with a large amount of zero bids, see Fig. 2.9(a). In some countries, as a means to promote their use, RES are paid directly through subsidies and are not traded on the wholesale market. Referring to the merit order, the effect is the same, since RES production can now be subtracted from demand and only the resulting residual demand has to be met by the conventional generators.

RES output varies with time depending on weather conditions, but, if it exceeds demand, then in principle a market clearing price of zero will be the result. However, due to the inter-temporal constraints described above and a number of other technical and non-technical complexities, prices can even become negative - this is a phenomenon that is already observed in systems with high amounts of renewables like Denmark and Germany. Box 1 describes the cases of negative wholesale prices in Denmark and Germany in more detail.

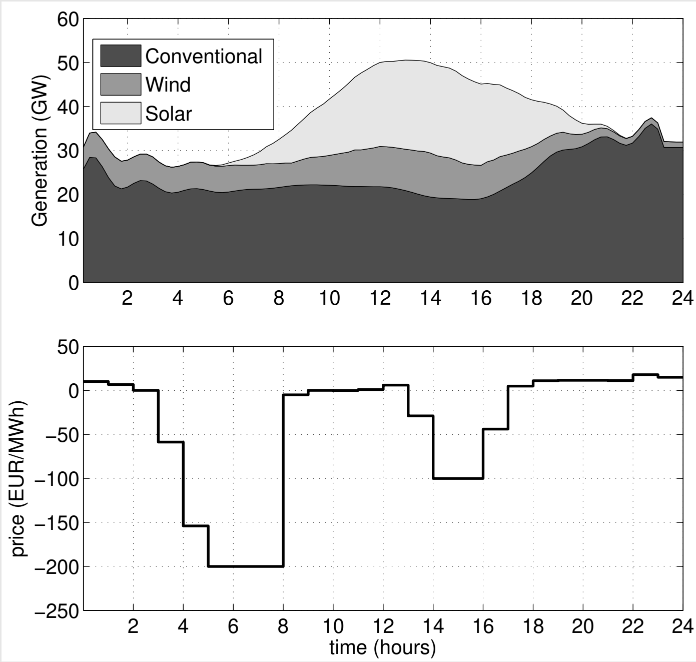
A high amount of renewables will thus create moments with very low, or negative electricity prices. Increased interconnection and flexible demand will, on the other hand, have a damping effect on electricity prices. Depending on the exact nature and physical characteristics of the flexible demand, it could, for example, be possible to shift a portion of the demand by several days. This would allow to anticipate on low prices caused by high RES output, and to schedule demand in those periods. Referring to Fig. 2.9(b), this would mean that the demand bids would be shifted to the right in case of a large amount of zero bids. The effect of the zero bids would thus be partially offset by the price responsive demand. Market coupling enabled by interconnectors has a similar, though slightly different damping effect on price.

Box 1 - Negative wholesale prices The figure below shows the demand, wind energy production and the resulting wholesale electricity price in the Western Danish System, for a period in spring 2012. One observes how prices briefly become negative in one of the periods where wind power exceeds demand. It is also interesting to note that in other periods with negative demand prices did not go to or below zero, indicating once more that the emergence of electricity price is a complex phenomenon and cannot only be explained by looking at the merit order and system demand. Among other things, exchange with neighboring systems, maintenance scheduling and the already mentioned inter-temporal constraints play an important role, too.



Demand, wind power and prices in the western Danish system in a period around April 1st 2012. Data from [24]

Box 1 - Continued More recently, Germany coped with an even extremer case of negative wholesale prices. On Sunday June 16th 2013, a very low system load coincided with a fairly large output of wind and solar power. The results was that the coal, lignite and nuclear generation units had to be ramped back to unusually low levels of approximately 20 GW. This led to a situation with extremely low wholesale prices of -200 €/MWh for a sustained period of time.



Conventional, wind and solar power and spot prices for the German system on June 16th 2013. Data from [25]

Distribution networks regulation Unlike the production and retail of electricity, transport and distribution are not subject to open competition in unbundled power systems. DSOs are responsible for the distribution networks and, since they form a natural monopoly in their service area, their activities are regulated. Some variations in the exact form of regulation are possible, but generally this means that the competition authority determines the (change in) tariffs the DSO is allowed to charge its customers for a certain period of time, referred to as the regulatory period. For instance, in the Netherlands this is 4 years. In the regulatory framework in the Netherlands and many other countries the change in tariffs is determined by the following formula:

$$TI_{t,i} = (1 + cpi_t - x_i + q_i)TI_{t-1,i} \tag{2.3}$$

where the $TI_{t,i}$ is the allowed total income of DSO i in regulatory period t, cpi is the consumer price index (a measure of inflation), x is the efficiency factor and q is the quality factor. The x-factor basically determines how much more efficient a DSO need to be in the next regulatory period. It is determined in a complicated way, accounting e.g. for differences between the service areas of the different DSOs, but the guiding idea is a benchmark that is set by the DSO with the lowest cost levels.

DSOs are in principle profit maximizing entities, but their income is determined by the regulator, so a profit maximizing objective implies that they will generally aim to minimize costs. Costs of a DSO are largely determined by CAPEX and OPEX on the assets, of which the former is dominant. Energy losses form an important part of OPEX related to assets. For instance, the 2012 annual report of Enexis, one of the three largest DSOs in the Netherlands, covering roughly 33% of the Netherlands, lists investments in assets as 247 M€ and costs of energy losses at 90 M€ [26]. Reducing investments in new or replacements of old assets and costs of energy losses are thus a vital tasks for DSOs in a regulated environment.

2.2 Electric vehicles

The following sections describe the role of EVs in future power systems. We present a model EV charging and the mobility data that is the input for these models. In addition, we describe how EV charging can be viewed as a mathematical optimization problem and we show how the optimization objectives depend on the perspectives of the actors involved in it. We start the chapter by an analysis that explores the various actors involved in EV integration and different institutional arrangements.

2.2.1 Actor analysis

Fig. 2.7(b) shows a schematic overview of an unbundled electricity sector in which a number of interacting actors can be distinguished. Below we briefly describe the actors that will play a role around EV charging. After that we describe three possible configurations in which EV charging could take place, each with different interactions between the actors. This analysis is partially based on [27] that gives a thorough and comprehensive description of different actors involved in EV charging and possible institutional/contractual arrangements. For a more elaborate treatment of this topic we thus refer to [27]. Next to the actors specifically involved in EV charging we also summarize the role of the other power system actors discussed in the previous sections.

- Generator (also referred to as electricity producer). Produces and sells electricity. Electricity sales can be either through various markets (day-ahead, intraday, balancing), or in bilateral contracts with suppliers or large consumers. Producers are balance responsible parties (BRPs), which means they have the obligation to comply with a production profile submitted usually 24 hours in advance.

- Supplier (retailer). Intermediate party selling electricity to end-consumers. Suppliers can own generation capacity, or buys electricity from generators through spot market or bilateral contracts. Suppliers are BRPs, too.

- DSO. Owns and maintains distribution networks. Regulated entity and legally unbundled from generation and retail of electricity. Consumers pay a grid tariff to DSOs included in their supplier tariff, who pays the DSO. Large consumers sometimes pay directly to DSO.

- TSO/ISO. Transmission system operator or independent system operator. Manages high-voltage transmission networks and is responsible for various other system functions. Maintains system balance, manages congestion, organizes different markets (day-ahead, intraday, balancing).

- Consumer (final customer). User of electricity. Connected mostly to LV distribution network, but large customers (industrial, commercial) can be connected at higher voltage levels. Has a contract with a supplier, and pays through supplier to DSO for grid access and taxes.

- EV owner. Owns (or possibly rents/uses) and charges an EV. Might have a contract with supplier or possibly an EV aggregator. Might have possibility to charge at home, or else at public or private charging stations.

- EV aggregator. Intermediate party between EV owners and other actors, most notably suppliers and/or other market parties and DSOs. Manages charging of a fleet of EVs and benefits from economies of scale through aggregation. Does not necessarily own or operate physical charging infrastructure.

- Charge point manager. Owns and operates physical charging infrastructure. Could have possibilities for smart charging strategies. Pays DSO and either suppliers or directly to the market for network capacity and energy.

Possible EV charging arrangements

Below we discuss a few possible configurations of EV charging. We loosely follow [27] who classify the different arrangements on three aspects: the location of the charging point, the intermediate actor between EV owner and other actors/functions in the system (e.g. DSOs, suppliers, ‘the market’), and the level op sophistication in the management of the charging process (uncontrolled, controlled). It is emphasized that more possible configurations are possible than discussed here. Furthermore, the different arrangements are likely to co-exist and even a single EV owner might charge in several different configurations.

Uncontrolled home charging Due to the lack of a large-scale EV charging infrastructure, many EVs are currently being charged at the EV owners home. In this scheme, depicted schematically in Fig. 2.10, the EV can be seen as simply another domestic electrical appliance without a special connection or meter and its energy is paid for through the regular electricity bill. One could say that the intermediate actor in this scheme is the same one as for the consumer: the electricity supplier. Since in most countries there are no advanced time of use tariffs, it is likely that most EV owners will start charging their car upon arrival at home. This scheme is therefore labeled uncontrolled charging, as opposed to the more advanced schemes where charging is controlled or postponed according to some objective.

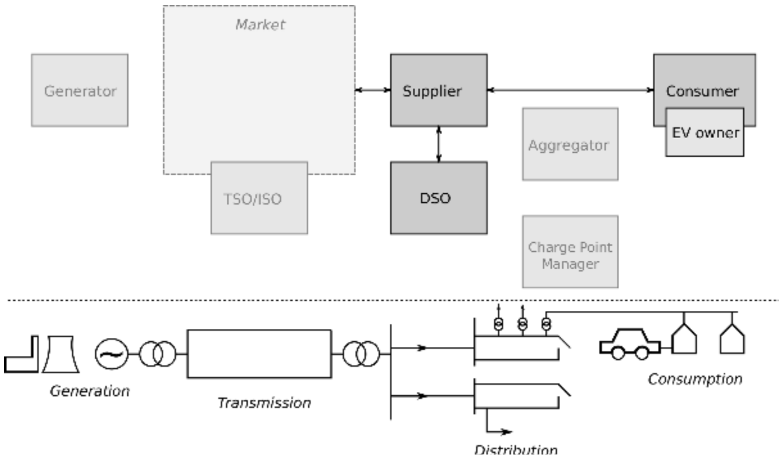


Figure 2.10 – Schematic view of economical and physical layers related to the uncontrolled charging scheme. Arrows denote exchanges of information and/or money.

Controlled home charging with aggregation A more sophisticated scheme than uncontrolled home charging is a configuration where charging physically still takes place at the EV owners home, but with an EV aggregator as intemediate actor. This scheme is depicted schematically in Fig. 2.11. More advanced metering infrastructure will likely be required in this configuration. Furthermore, EV owners without private parking spaces like a garage or driveway could use a public space charging point near their house. The aggregator benefits from economies of scale and more predictable demand patterns through the process of aggregation. He will purchase energy from the (various) market(s) and could optimize EV charging in order to reduce energy costs. Possibly the aggregator still has energy contracts with the conventional suppliers of electricity. In more advanced schemes the aggregator can even offer regulating power to balancing markets, or other products based on EV charging flexibility. Of course, any form of controlled charging would need to be within boundaries indicated by the EV owner. Such boundaries are technical specifications like the power and battery limits on EV charging, but more importantly the individual preferences in terms of driving needs. Differentiated tariffs with respect to costs, priority and speed of charging, environmental aspects, etc, could be possible. Aggregators could have direct contractual relationships with DSOs, or, alternatively, this can be via the electricity suppliers.

Controlled charging in a charging station Another form of EV charging that may emerge as the number of EVs grows is charging at a dedicated charging station, shown in Fig. 2.12. Various different settings are possible, ranging from e.g. a single charging point in an office parking lot to complete charging stations with multiple charging points and possibilities for fast charging. The latter would resemble current day gasoline stations to some extent. The actor that owns and manages the charging station or single charging points was named the charge point manager (CPM) in [27]. The CPM could also engage in controlled charging strategies, pos-

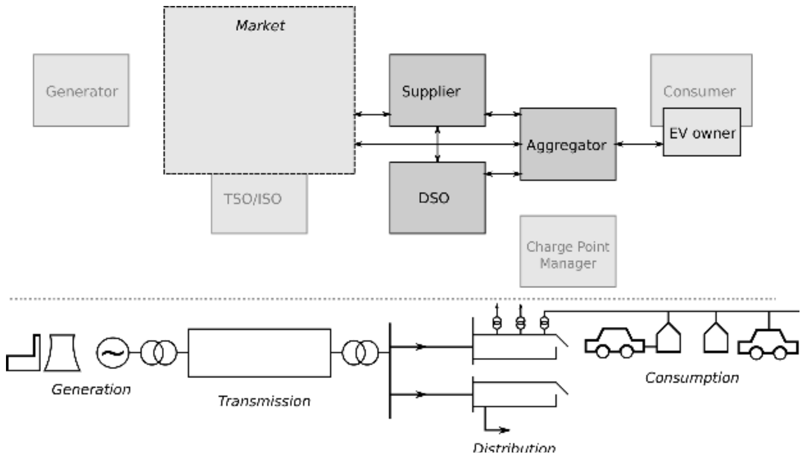


Figure 2.11 – Schematic view of economical and physical layers related to the controlled charging with aggregation scheme.

sibly enabled by on-site distributed and/or renewable generation and energy storage technologies. The CPM has a contractual agreement with the DSO for network capacity. Such contracts could be based on ToU tariffs, or more advanced dynamic grid tariffs[4]. Depending on the number of charging points in the charging station, an MV connection together with a MV/LV transformer might be required. In addition to network related contracts, the CPM also manages energy sales, either through a supplier or by directly interacting with the market and/or generators. Time-varying wholesale prices, the intermittent character of installed on-site RES generation and dynamic grid tariffs could all be incentives for the CPM to charge time-varying charging rates. To the extent forecasting allows it, these could be announced ahead of time. Drivers can then plan when to enter the charging station. In this way, the combined demand of many charging stations might still exhibit the elasticicity that is beneficial for the electricity system.

Simplified arrangements treated in this thesis

The different charging configurations described in the previous section are already a gross simplification of the complex interplay between different actors that would be observed in reality. Nevertheless, many of these inter-relations between actors are considered to be outside the scope of this thesis, and simplified institutional arrangements are therefore assumed. Since different chapters have different perspectives on EV charging, a number of simplified configurations are assumed, see Fig. 2.13. In chapter 4, where the impacts of EV charging on distribution networks are assessed, the DSO is assumed to have control over the charging process. In this sense, only the interaction between EV owners and the DSO is relevant, as depicted in Fig. 2.13(a). In chapter 5, on the other hand, EV charging is controlled from the perspective of lowering generation costs by including EV charging as decision variable

[4] See chapter 6 for a more elaborate discussion on this topic

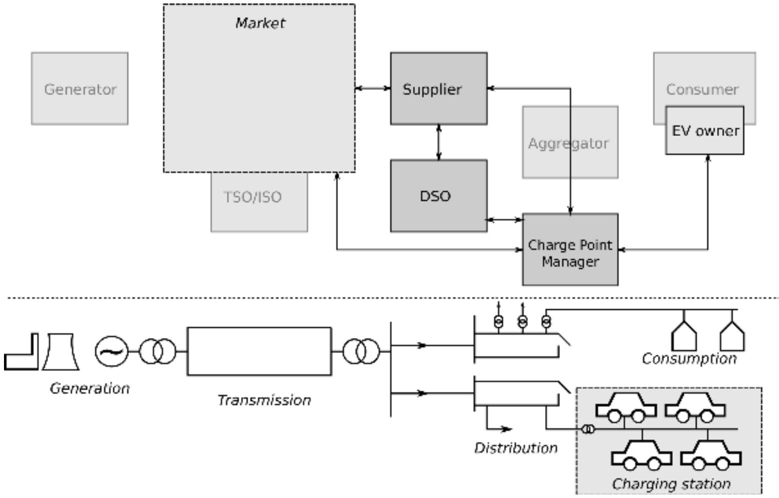


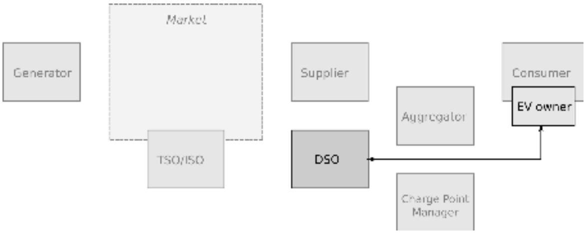
Figure 2.12 – Schematic view of economical and physical layers related to the controlled charging in charging station scheme.

in a unit-commitment model. Here, all complexities regarding markets, intermediate actors and distribution networks are ignored. In this perspective only the interaction between generation units and the EVs is of importance, as shown schematically in Fig. 2.13(b). Yet another perspective is found in chapter 6. Here it is assumed that EVs are charged based on wholesale market prices. Furthermore, information exchange between EVs and the DSO is assumed. In addition, in this chapter the role of the aggregator is treated more prominently. This simplified arrangement is schematically sketched in Fig. 2.13(c). Chapter 7 investigates additional aspects of EV charging, but mostly from the perspective of the arrangement depicted in Fig. 2.13(c).

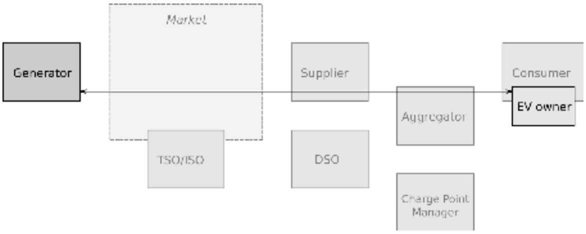
While the institutional arrangements regarding smart EV charging are not the main topic of this thesis, and therefore strongly simplifying assumptions have been made to represent them, this approach does provide useful insights on how such arrangements could be organized. In this sense, the analyses from this thesis can be considered as input for more detailed studies on the institutional aspects of EV charging. Eventually, such studies should lead to a meaningful institutional arrangement where the potential of EVs can fully contribute to the realization of future sustainable energy systems.

2.2.2 Driving data

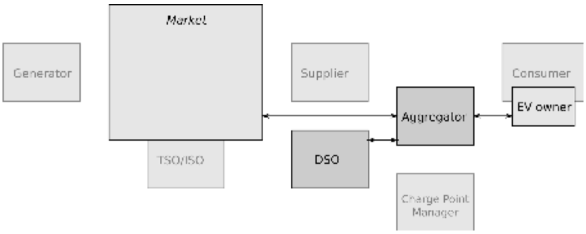
The following section describes the driving data that has been used to model EV demand profiles throughout this thesis. A more detailed description can be found in [28]. The Mobility Research Netherlands gives a large dataset of individual trips by various transport means. The data is collected by means of a survey of roughly 40.000 people in the Netherlands [29]. The dataset consists of over 130.000 individual movements (one way trips), from which approximately 40.000 are car movements of



(a) Chapter 4



(b) Chapter 5



(c) Chapters 6 and 7

Figure 2.13 – Simplified institutional arrangements assumed in different chapters of this thesis

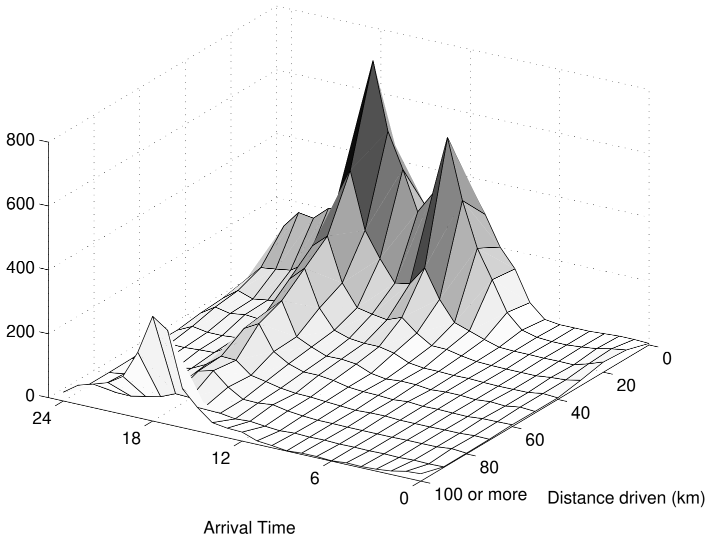


Figure 2.14 – Joint distribution of home arrival times and daily driving distances. Values on the z-axis denote the number of occurrences in the dataset of approximately 18.000 individual drivers.

roughly 18.000 individuals. Important variables for EV charging are (for each of the 18.000 individual cars): daily driving distance, home arrival time and home departure time.

To get some insights in the driving patterns, Fig. 2.14 shows the distribution of car trips based on daily driving distance and the time at which the *last* arrival at home takes place. From Fig. 2.14 it can be concluded that on average, the majority of car drivers covers only modest distances. Furthermore, it is noteworthy that the distribution of the shorter trips shows two distinct peaks, one around noon and one around 1800h. Apparently, a significant fraction of the people tend to use their car only during the morning, since we have considered only the *last* arrival time at home. For the longer distances, the time of the last arrival at home is mostly in the early evening or late afternoon. This can intuitively be understood by considering the daily commuting cycle of driving to work in the morning and arriving back home in the evening.

2.2.3 EV battery model

In the following section we present a simple model of an EV battery, with the objective of relating technical battery parameters, the energy needed for driving and the power demand of the EV as seen from the grid. More detailed models on EV batteries can e.g. be found in [30], [31] and in [32].

The *state-of-charge* of a battery is a dimensionless number representing the charge content of a battery and is defined as:

$$SoC(t) = \frac{Q(t)}{Q_0} \tag{2.4}$$

where $Q(t)$ (with units Ah) is the amount of charge at time t and Q_0 is the nominal capacity of the battery in Ah. Differences in SoC due to charging or discharging within a period from t_0 to t_f are given by:

$$\Delta SoC = \frac{1}{Q_0} \int_{t_0}^{t_f} I(t)dt \tag{2.5}$$

For various numerical simulations on EV charging it is convenient to use a discretized version equation 2.5 and to use *energy content* rather than SoC . If we assume a constant battery voltage V_{batt} and charging/discharging with a constant current, we can write the following expression for the energy content $E_{EV,k} = Q_k V_{batt}$ at time-step k of the EV battery:

$$E_{EV,ik+1} = E_{EV,ik} + P_{batt,ik}\Delta t \tag{2.6}$$

where $P_{batt,ik} = I_{ik}V_{batt,ik}$ denotes the power flow into or out of the battery and subscript i identifies different EVs. There are, however, various losses associated with charging or discharging a battery.

Discharging Most notably, the battery capacity Q_0 actually depends on the magnitude of the discharge current, and hence on the driving behavior. We are, however, most interested in the EVs from the point of view of the electricity grid, and not in the processes taking place while driving. Therefore we define a constant driving efficiency η_d with units km/kWh. One way to estimate the value of this parameter is to compare the nameplate battery capacity with the reported range of the vehicle. In [33] a number of different values for the range of a Nissan Leaf - one of the standard EV models on the market today - with a battery capacity of 24kWh is reported. These are the results of different tests under different driving conditions. We assume a rather conservative range of 120km, which yields a driving efficiency of $\eta_{d,i} = 5\,\text{km/kWh}$.

We can now readily relate the discharges d_{ik} (battery discharge due to driving) to driving patterns L_{ik} (number of kilometers driven at time-step k):

$$d_{ik} = \eta_{d,i}L_{ik} \tag{2.7}$$

The driving patterns L_{ik} are modeled based on the mobility data presented in the previous subsection.

Charging Charging of EVs is also associated with inefficiencies such as inverter losses and various losses inside the battery. Although some of these losses depend on the magnitude of the charging power, we assume a constant charging efficiency η_c . Often, however, only round trip efficiencies of a charge-discharge cycle are reported. In [34], a round trip efficiency of 85%, resulting in a charge efficiency of $\sqrt{0.85} \approx 0.93$, is assumed, although it is also noted that laboratory experiments showed a DC-DC round trip efficiency of over 95%. Now from the point of view of the grid, the power drawn by the EV and the power actually flowing into the battery are related by $P_{batt,ik} = \eta_c P_{EV,ik}$. The complete equation that relates battery energy content of EV i to its charging power and driving patterns is thus given by:

$$E_{EV,ik+1} = E_{EV,ik} + \eta_c P_{EV,ik} \Delta t - \eta_{d,i} L_{ik} \tag{2.8}$$

2.2.4 Uncontrolled charging

The dataset of driving patterns described above provides the basis for controlled charging strategies described later in this thesis, but also for an uncontrolled charging scenario that has an important function as reference case to compare other scenarios with. The uncontrolled charging scenario assumes that people will charge their EV at home, every day after the last arrival of the day. The exact shape of the power profile drawn by a single EV will differ per vehicle, depending on factors such as the battery type and the battery management system. Common charging profiles start with a phase of constant current and end with a phase of constant voltage, see e.g. [30]. Some vehicles have fast charging capabilities that yield even different power profiles.

A simple approximation to real observed charging profiles would be to assume constant power charging throughout the complete charging process. If this constant power charging is fixed at a certain value, an individual EV charging profile is completely determined by the amount of energy that needed to be recharged. With the assumptions stated above (charging at home after last arrival), the profile of single EV is hence a block starting at home arrival time, with a height equal to the fixed power and a width such that the area (which denotes energy) is corresponding to the daily driven distance. Adding many of these blocks yields the profile of a group of EVs as depicted schematically in Fig. 2.15.

The profiles constructed in the way described above can be used to represent the demand of a group of EVs of any given size if they are scaled appropriately. This means that the shape of the profile is assumed to be independent of the number of EVs, but the magnitude is scaled according to the energy demand of the EVs. For very low numbers of EVs this approach will not be accurate, since the profiles have a more spiky shape. The question is for how many EVs one can assume that the aggregate profile will be a good approximation. Fig. 2.16 shows the simultaneity factor defined by Eq. 2.1 as a function of the number of EVs. We conclude that this approach is more or less valid if the number of EVs considered is larger than approximately 50.

Furthermore, from Fig. 2.16 we can also deduce how the combined peak load of a group of EVs depends on the charging power of the individual EVs. The higher the charging power, the shorter the time needed to recharge the battery and, hence, the lower the probability that charging of different EVs overlaps. For a charging power of 10 kW, the simultaneity factor approaches a value of 0.1, which implies that the combined peak of, say, 1000 EVs charging with 10kW is only 1000kW. This number, which is based on actual driving patterns, is an order of magnitude lower than what

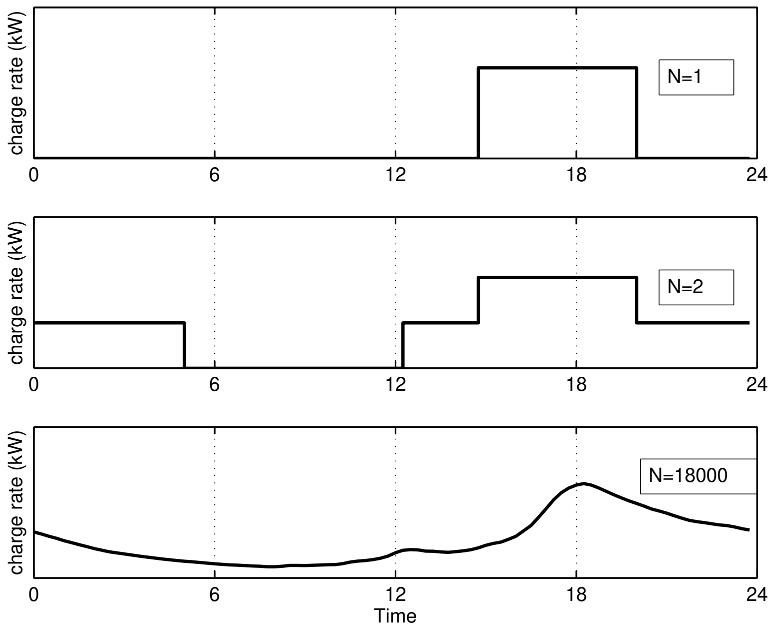


Figure 2.15 – Schematic representation of the construction of the aggregated charge profiles from individual car energy needs in the uncontrolled, 3kW charging scenario

a calculation that simply assumes all EVs will be charging at the same time would yield.

2.2.5 Electric vehicle charging as optimization problem

Eq. 2.8 relates the battery state of energy to discharges due to driving. Taking into account the battery limits on energy and power, one observes that the charging process inhibits some flexibility - the time dependent charging power $P_{EV,k}$ can in principle be chosen freely, as long as the energy content allows for making the planned trips L_k. Due to this flexibility, EV charging can be approached as an optimization problem, where the challenge is to find a charging schedule $P_{EV,k}$ to minimize some objective. The constraints of the optimization problem are given by the battery energy and power limits, in combination with Eq. 2.8 that relates the optimization variables P_k with the battery state-of-energy. In the following section we will discuss a number of possible charge strategies that result from different objectives of different stakeholders in liberalized power systems. For the theoretical foundations of mathematical optimization a large body of literature exists, see e.g. [35], [36] and [37]. The optimization formulations discussed below are discussed in more detail in [38].

Aggregators as price takers An aggregator representing a number of EV owners has the task to charge the EVs while taking into account the driving patterns of the EV owners. We will consider here only the case where the objective is

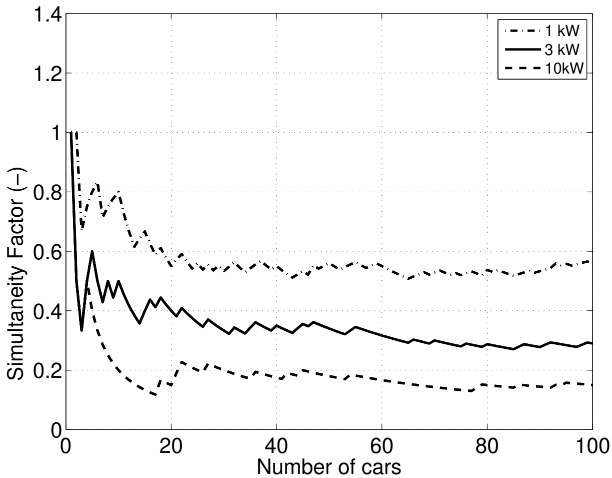


Figure 2.16 – Simultaneity factor as a function of the number of cars.

to minimize the charging costs of EVs, although, of course, other strategies could be envisioned as well. First the aggregators are modeled as price takers, i.e. the combined demand of the EVs does not influence market prices. The optimization problem then takes the following form:

$$\min_{P_{EV,ik}} \sum_{k=1}^{N_k} \sum_{i=1}^{N_{EV}} \lambda_k P_{EV,ik} \tag{2.9}$$

$$\text{subject to} \quad E_{EV_{min},i} \leq E_{EV,ik} \leq E_{EV_{max},i} \quad \forall i,k \tag{2.10}$$

$$P_{EV_{min},i} \leq P_{EV,ik} \leq P_{EV_{max},i} \quad \forall i,k \tag{2.11}$$

with λ_k the (anticipated) real time electricity price. The battery parameters $E_{EV_{max},i}$, $E_{EV_{min},i}$, $P_{EV_{min},i}$ and $P_{EV_{max},i}$ are given for each EV.

The battery state equation given by Eq. 2.8 is repeated here in slightly different format:

$$E_{EV,ik+1} = E_{EV,ik} + \eta_c P_{EV,ik} \Delta t - d_{ik} \tag{2.12}$$

This equation can be used to express the constraints 2.10 solely in terms of the optimization variables $P_{EV,ik}$. Note that in this formulation a driver only has to specify his driving schedule (the values of d_{ik}) and never finds his battery empty. If desired, the minimum battery level $E_{EV_{min},i}$ could be raised by a certain safety margin, for example to always allow an EV driver to reach a fast-charging station.

If necessary, an additional constraint can be added to require the battery being full at the end of the considered period, or, alternatively, one could assign a cost to a not fully charged battery at the final step. In the simulations discussed in the later chapters we have added an inequality constraint to make sure the battery state of charge at the end of the optimization horizon, denoted with time T, was at least as full as at the beginning:

$$E_{EV,iT} \geq E_{EV,i0} \quad \forall i \tag{2.13}$$

Problem 2.9 with constraints 2.10, 2.11 and 2.13 form a linear programming problem.

Aggregators influence market prices Now we consider the situation where an aggregator charges a number of EVs, but the aggregate demand of the EVs is such that it influences market prices. Market prices are modeled to depend linearly on the total electricity demand. Demand of electricity $P_{D,k}$ is given by:

$$P_{D,k} = P_{D0,k} + P_{EV,k} \tag{2.14}$$

where $P_{D0,k}$ is the original demand and $P_{EV,k} = \sum_i P_{EV,ik}$ is the extra demand of the EVs. Note that from now on we replace $P_{EV,ik}$ by $P_{EV,k}$ in the optimization formulations, but the optimization is still done with the individual $P_{EV,ik}$ as variables.

If the market price of electricity is assumed to be some function of demand $\lambda_k = \lambda(P_{D,k})$ then a first order Taylor approximation of the electricity price for a certain period is given by:

$$\lambda(P_D) \approx \lambda(\bar{P_D}) + \lambda'(\bar{P_D})(P_D - \bar{P_D}) \tag{2.15}$$

where the overbar denotes averaging over the period under consideration. After substitution of Eq. 2.14 in Eq. 2.15, the expression for λ_k can be written as:

$$\lambda_k = \alpha_k + \beta P_{EV,k} \tag{2.16}$$

with

$$\alpha_k = \lambda(\bar{P_D}) + \lambda'(\bar{P_D})(P_{D0,k} - \bar{P_D}) \tag{2.17}$$

$$\beta = \lambda'(\bar{P_D}) \tag{2.18}$$

The coefficient β represents the sensitivity of electricity price to demand. It can for example be estimated using statistics of historical data, see e.g. [39]. Here we use the exponential fit of the merit order that is shown in Fig. 2.17.

With these definitions, the optimization problem takes the following form:

$$\min_{P_{EV,k}} \sum_{k=1}^{N_k} \alpha_k P_{EV,k} + \beta P_{EV,k}^2 \tag{2.19}$$

with the same constraints as in 2.10, 2.11 and 2.13 and the battery state equation 2.12. This is a quadratic programming problem. If desired, methods to include non-linear price dependencies can be implemented. Such methods will generally require iterations where price parameters are updated after each iteration step, see e.g. [39].

Fig. 2.18 shows an example solution of the optimization problem 2.19 with constraints 2.10, 2.11 and 2.12 for two different EVs, one with a small daily driving distance, one with a large daily driving distance. The aggregate load of a large fleet of EVs, approximately half of the total passenger car fleet in the Netherlands, on the Dutch electricity demand can be seen in Fig. 2.19. As expected, the EV demand is scheduled mainly during the night hours with low prices. It can be seen that the EV demand 'fills' the demand profile in the night, so that a much flatter profile results.

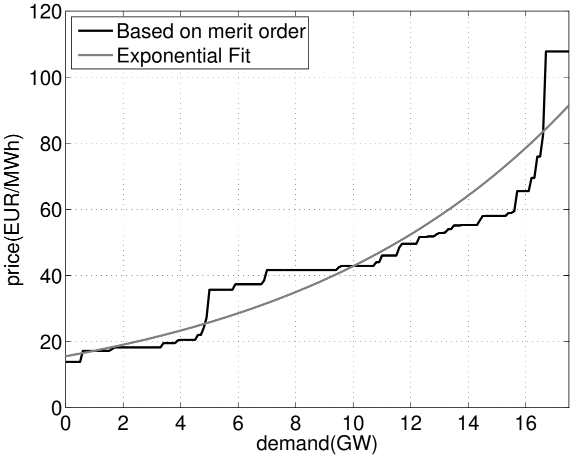


Figure 2.17 – Supply curve in the Netherlands and exponential fit.

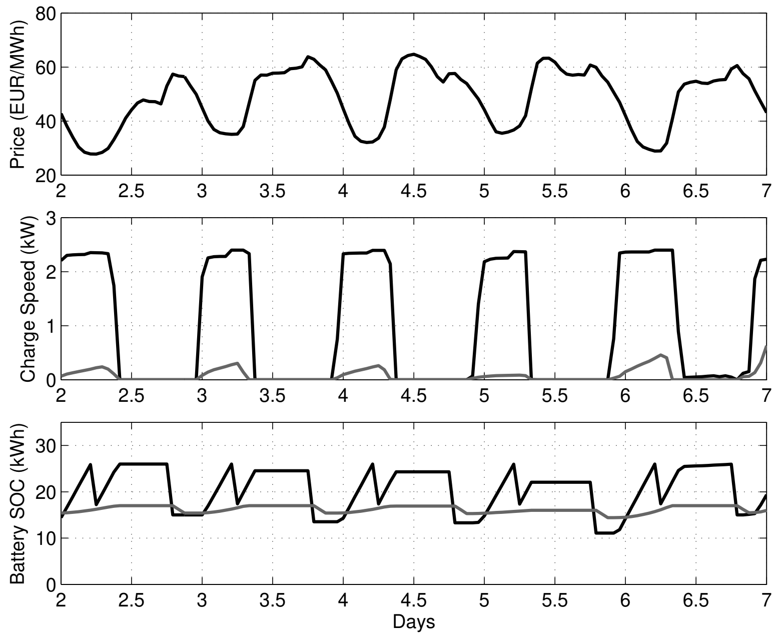


Figure 2.18 – Example of the quadratic programming formulation of the minimal charging costs problem where EVs are modeled influencing market prices. From top to bottom: electricity price, battery power, battery state of charge. Two different driver types are plotted: the grey line corresponds with a driver with a low daily driving distance, the black with a large daily distance.

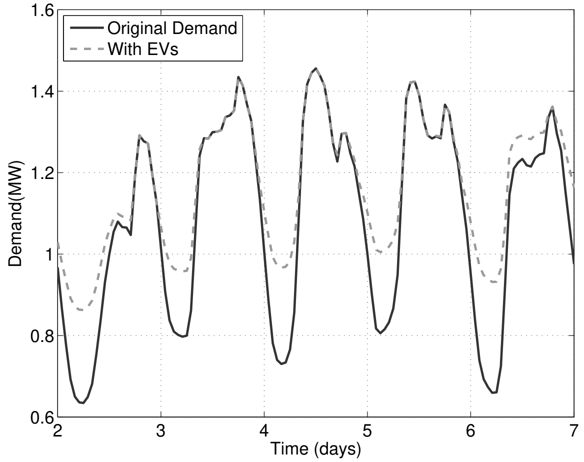


Figure 2.19 – Original demand and EV demand resulting from the quadratic programming formulation of the minimal charging costs problem where EVs are modeled influencing market prices. The EV demand corrseponds with 3.5 million EVs or approximately 50% of the total passenger car fleet in the Netherlands.

DSO: Minimize peak load and network losses If a distribution network operator were to control charging of EVs, its objective will generally be to minimize losses and reduce (or at least not increase) peak loads. It can be shown that, under most circumstances, an as flat as possible load profile will fulfill these objectives [40]. The optimization problem can then be defined as follows:

$$\min_{P_{EV,kl}} \sum_{k}^{N_k} \sum_{l}^{N_l} R_l (P_{l,k} + P_{EV,kl})^2 \tag{2.20}$$

where index l is used to denote different lines, $P_{EV,kl}$ is the EV load on line l and R_l is the resistance of line l. In principle this formulation is also valid for transformers. The same constraints dictated by individual driving behavior and battery limits as defined in Eqs. 2.9 to 2.13 apply. With these constraints and objective function Eq. 2.20, this, too, is a quadratic programming problem. If desired, additional constraints on network limits can be incorporated.

Fig. 2.20 shows the aggregate network load on a distribution asset together with the EV demand scheduled on the basis of optimization problem 2.20. Here EV demand, much like the previous case, is scheduled exactly in the hours with the lowest network load. However, because network load on a distribution cable has a different profile than national electricity demand, the resulting EV demand also differs. This difference in perspective and its possible consequences are the main subject of chapter 6. Chapter 4 will mainly focus on the impacts of EV charging on the distribution system and how controlled EV charging can relieve those impacts. In principle, the EV demand resulting from the formulation given in 2.20 should be used to minimize the distribution system impacts, but in chapter 4 a slightly different approach was used, which does, however, lead to a similar EV demand

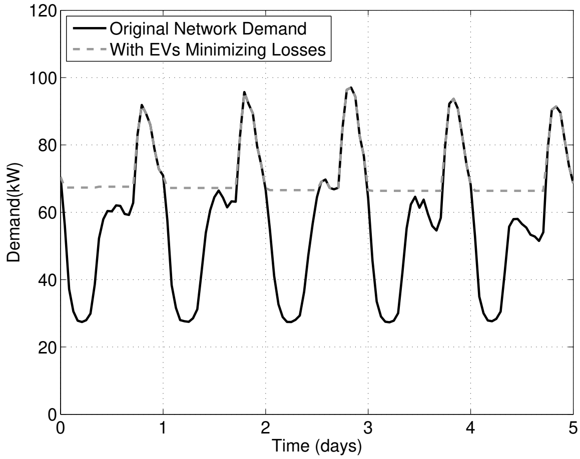


Figure 2.20 – Network load and EV demand for the quadratic programming formulation of the minimal energy losses problem.

profile. Chapter 5 deals with the problem of including EV demand scheduling in the optimization of power plant outputs, the so-called *unit commitment* problem.

Chapter 3

Literature review

This thesis is about the integration of electric vehicles in power systems with a large amount of renewable energy sources. This topic does, however, cover such a large range of scientific aspects, that it is hard to sketch a complete picture of the scientific literature describing this area. We will nevertheless attempt to give an adequate overview, and identify the knowledge gap that this thesis aims to fill. Following the lines of this thesis, we will focus on EVs and the distribution grid on the one hand, and EV impacts related to renewable energy on the other hand. How this thesis should be viewed in perspective of the scientific literature is described in more detail at the end of this chapter. Next to this more general literature analysis, the core chapters 4, 5 and 6 provide in their introductory texts an analysis of the literature of their specific topics.

3.1 Trends in literature on the role of EVs in smart grids

The topic of this thesis can, somewhat arbitrarily, be defined as EVs in smart grids, both from a point of view of the grid and the integration of RES. We are therefore interested in literature in a field spanned by the following query:
`EVs AND Smart Grids AND (RES OR Grids)`

However, since, on the one hand, different authors use many different terms and keywords for the same things, and, one the other hand, 'smart grid' is a very broadly defined notion, we use, after some trial and error, the following query in Scopus[1] to arrive at a list of articles that, in our opinion, contains the most relevant literature:

```
TITLE-ABS-KEY(
("Electric vehicle" OR EV OR PHEV OR "Electric transportation") AND
("smart grid" OR "demand response" OR "load management"
OR "responsive demand" OR V2G OR "vehicle-to-grid") AND
(("Renewable energy" OR wind OR solar OR "stochastic generation")
```

[1]Although other knowledge databases than Scopus are available, and Scopus does not cover everything, we consider the query results sufficiently complete as a basis for this literature analysis.

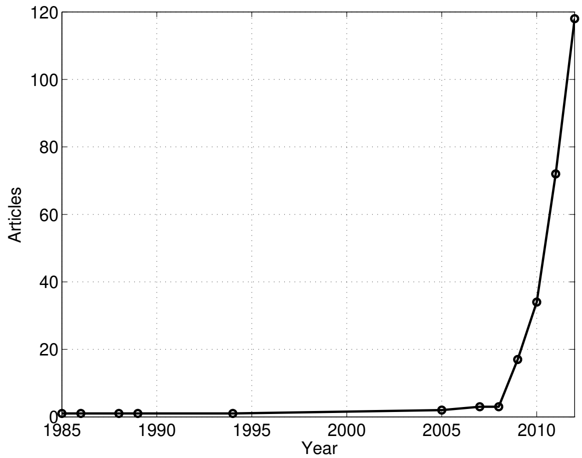


Figure 3.1 – Trend in the number of articles concerning of intelligent EV management.

```
OR ((power OR electricity OR distribution) AND (grid OR system OR network))))
AND (LIMIT-TO(DOCTYPE, "ar"))
```

We discuss some meta-level aspects of this literature list first, and then we discuss some of the most important papers individually.

The query result counts 293 articles.[2] Fig. 3.1 shows the number of records of the above query per year until 2012. Clearly, this is a very new topic: the number of articles from before 2009 is very low. The articles from 1994 and earlier turned out to be on battery chemistry and were thus not so relevant in the light of this thesis. Interestingly, the two earliest after that (from 2005) were also the most cited articles from the list: [41] and [42], see also Table 3.1. One could conclude from this that these articles really were the pioneering work that paved the way for many other researchers - including the author of this thesis.

We observe from the other studies mentioned in Table 3.1 that they cover quite a broad range of topics: from distribution grid impacts to frequency regulation. Looking more closely at the complete list of 293 papers that form the query result, one could make an attempt to define sub-fields. In Fig. 3.2 one such attempt of a division of the completely field in subfields is shown, with some of the key papers indicated that we will discuss in more detail in the next section. They are encoded by the the first three letters of the first author and the year of appearance. The figures shows two axes: the y-axis that ranges from 'technical detail' to 'system view' and the x-axis that ranges from 'RES integration' to 'EV integration'. There is a degree of arbitrariness in this division, but in the light of this thesis we consider it meaningful. Another possible categorization was made in the overview article of [50]. There, the distinction is made between 'EV grid models', 'EV impacts' and 'EVs and renewables', which were each further divided in lower categories.

[2]When performing this query in June 2013.

Table 3.1 – Most cited journal articles concerning intelligent EV management.

First Author, Year, Reference	Citations	Title
Kempton2005, [41]	434	Vehicle-to-grid power fundamentals: Calculating capacity and net revenue
Kempton2005a, [42]	403	Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy
Ipakchi2007, [43]	297	Grid of the future
Clement-Nyns 2010*, [44]	289	The impact of charging plug-in hybrid electric vehicles on a residential distribution grid
Tomić2007 [45]	219	Using fleets of electric-drive vehicles for grid support
Lund2008 [46]	159	Integration of renewable energy into the transport and electricity sectors through V2G
Guille2009 [47]	152	A conceptual framework for the vehicle-to-grid (V2G) implementation
Han2010 [48]	137	Development of an optimal vehicle-to-grid aggregator for frequency regulation
Peterson2010 [49]	97	Lithium-ion battery cell degradation resulting from realistic vehicle and vehicle-to-grid utilization
Sortomme2011 [40]	92	Coordinated charging of plug-in hybrid electric vehicles to minimize distribution system losses

* Did not appear in the Scopus query result, but was added to the list because it is one of the most cited papers by all other papers in this field.

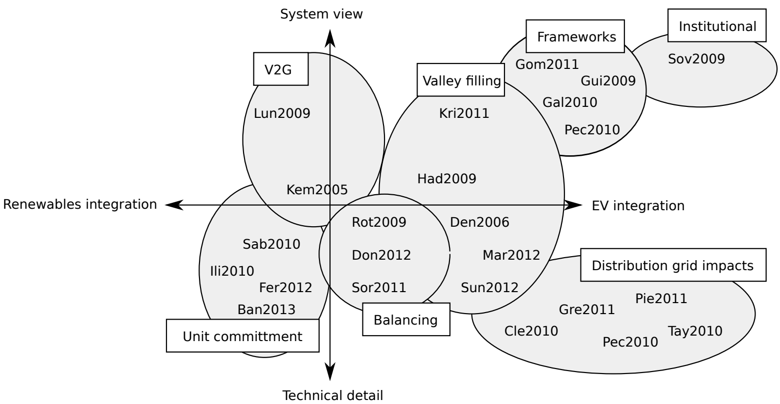


Figure 3.2 – Schematic overview of the scientific literature around the topic of EV and renewable integration.

3.2 Discussion of some important papers per sub-field

In this section we will discuss some of the most relevant articles from the field described above. We will do so according to the sub-fields of Fig. 3.2. Furthermore, we note that not all articles we discuss were found in the list of 293 that resulted from the Scopus query. In the following discussion we also indicate per paper the three letter year combination that was used in Fig. 3.2.

Vehicle to grid The work described in [41] (Kem2005) and in the accompanying article [42] could be considered as the first to investigate the potential of EVs and RES integration. These articles describe the first systematic exploration of the vehicle-to-grid concept, since then often referred to as V2G. It should be noted, however, that the first mention of this idea was already in earlier work [51]. The more recent articles [41] and [42] quantify the potential for V2G to participate in ancillary service markets and high values up to 4000$ per vehicle per year are found as potential revenues for offering such services.

In [46] (Lun2008), the benefits of V2G in a power system with a very high RES penetration were assessed. The main advantages are a sharp decrease of excess wind production and a strong reduction of CO_2 emissions. The latter can mostly be understood from a replacement of gasoline by clean electricity as fuel for vehicles. [46] considered a number of EV scenarios, which are, in increasing order of complexity: uncontrolled charging, intelligent charging without discharge and, finally, V2G, where EVs were allowed to discharge to the grid. Interestingly, almost all benefits are already realized in the intelligent charging without V2G, leading to the conclusion that the possibility to postpone demand to high wind periods is more important than the possibility to store and discharge electricity from the EVs.

In [49] (Pet2010) the economic potential of V2G for energy arbitrage purposes considering PJM wholesale prices is investigated. Noteworthy is the fact that they include realistic battery degradation costs to their analyses, that were determined in laboratory experiments described in [34]. Due to these relatively high degradation costs in combination with a small price spread in the PJM market, they find very modest, if not negligible V2G revenues.

Valley filling A number of studies have evaluated the potential to dispatch EV demand in the hours with low electricity demand[3], since this is generally considered to have a positive system impact. Most studies do this through the signal of electricity wholesale prices since these should in principle reflect the magnitude of electricity demand, others use more direct load scheduling algorithms.

[39] (Kri2011) discusses optimal EV charging based on Danish wholesale prices. Important contributions of this work are that the effect of the extra EV load on wholesale prices is taken into account, which leads to a quadratic programming

[3]This is often referred to as 'valley filling' to distinguish it clearly from 'peak shaving' which would only be possible in a V2G setting, i.e. vehicles delivering energy to the grid.

problem. In addition to this, a method to group EVs by driving patterns is introduced to make computations tractable.

One of the earlier studies to optimal EV charging from the point of view to ‘fill the valley’ of electricity demand was done by [52] (Den2006). Instead of the more frequently used mathematical programming tools, they use a ’valley-filling algorithm’ that assigns EV load to the moments with low demand. They show, using load duration curves, that EVs can indeed be charged in such a way that only base-load is increased and peaks do not change.

In [53] (Mar2012) the intelligent control of a parking lot with a fleet of EVs was considered. Interesting in this setup is that the vehicles can also deliver energy to each other (denoted with vehicle-to-vehicle, V2V), preventing to pay an extra grid fee for delivering energy back to the grid as in the ‘standard’ V2G setting. Spanish wholesale prices were used for the time varying energy tariff, and it was found that in their particular case study setting, there was a cost reduction compared to dumb charging, but V2V and V2G were found not to be profitable.

Integration frameworks A number of papers have treated the subject of how EVs and its smart management should be embedded in the current technical and organizational structures of power systems. Usually these type of studies formulate it as presenting a ‘framework’ for EV (or V2G) integration. Such studies usually have a rather abstract or general character, which is the reason why they have been placed at the top of Fig. 3.2.

One of the earlier works to present such a framework is described in [47] (Gui2009). They identify load leveling (‘valley filling’), regulation power and reserver power as the most important aspects in which EVs could provide value. Then possible approaches for the information, communication and control infrastructures are discussed. The aggregator, as the intermediate and coordinating entity between individual EVs and other stakeholders, plays a central role in this framework.

A second paper on EV integration frameworks is [54] (Gal2010), which, one could argue, goes somewhat further than [47]. Interestingly, when discussing the possible role of EVs in power systems, a remark is made that for an EV aggregator, although playing a central role, it is not quite clear yet on which layer of the power system structure (generation, transmission or distribution) or in which markets and with what actors they will interact mostly - a notion that is highly relevant for this thesis as well. One of the main ideas put forward in [54] is the operational framework based on a state description for the EVs, similar to states of a power system like ‘normal operation’ or ‘emergency’. In this framework, possible EV states are for example ‘charging’, ‘driving’, but also ‘feeding power’, as the framework incorporates V2G. The framework is demonstrated with an example case study where EVs are providing regulation services.

A comprehensive analysis discussing a conceptual regulatory framework as well as new business models for charging EVs is given in [27] (Rom2011). A variety of different settings of infrastructures, actors (denoted ‘agents’ in the paper) and commercial relationships are explored in-depth. The paper distinguishes two new actors that will be involved in EV charging besides EV owners: EV aggregators, denoted as EV supplier aggregator (EVSA), and charge point managers (CPMs).

One of the difference between these two is that the contracts of the EVSA are 'not location based or bound to a single outlet'. The aggregator benefits from aggregation advantages and economies of scale, but the EV owners it has contracts with are dispersed geographically. The CPM, on the other hand, owns and operates physical charging infrastructure on private property. The latter is an important distinction. Here it is the CPM who buys energy and/or network capacity and thus has to deal with DSOs and suppliers (or the market). Besides the various instutional arrangments also technical properties of different charging modes are discussed. V2G services are considered only to be feasible for the longer term. For the shorter term, three possible arrangements are considered as the most likely: 1) uncontrolled charging at home without any EVSA or CPM (basically what many of the early adopters are doing now) 2) controlled charging in public areas with an EVSA as intermediate and 3) controlled charging in private areas with the CPM as intermediate.

Another EV integration framework is presented in [55] (Pec2010). In the same paper, the authors also perform some technically detailed studies regarding possible voltage problems and the potential of EVs to enhance dynamic stability in isolated power systems. This twofold perspective is reflected in Fig. 3.2 where the same paper can be found both at the very bottom and the top of the figure. The most distinctive feature of the framework proposed in this paper is to distinguish explicitly between a technical and a market domain. The idea is that EVs can provide services to market participants, or benefit from certain conditions on the markets, only as long as they do not violate technical constraints. Following this philosophy, it is the DSO (responsible for the technical side) who can override the aggregator signals focusing on the market domain. One could thus argue that this framework ascribes more power to DSOs than in other frameworks, or, more importantly, than is allowed in some unbundled power sectors where a DSO is more or less obliged to facilitate and cannot interfere with the market. New possible organizational models to align technical distribution network limits with market signals are also discussed in chapter 6 of this thesis.

Finally we note that the papers [56] and [57] (Ili2011) that we discuss more in-depth below in fact also provide frameworks of EV integration, although their scope extends beyond EVs specifically. A common element with other frameworks is the key role of the aggregator. Compared to the other frameworks, [56] and [57] provide a valuable contribution by more explicitly focusing on the potential of flexible demand in the light of RES integration. Furthermore, the level of technical and mathematical detail can be considered much higher than especially the first two papers discussed in this subsection.

Institutional and social aspects Since, during recent years, EVs have started to become a promising and possibly high impact new technology, its adoption has been subject of many social science oriented papers as well. Since this perspective is not really the viewpoint of this thesis, we will only discuss one of the earlier and mostly cited paper in this field, which is [58] (Sov2009). The paper discusses the benefits and potential barriers of large EV adoption and a V2G transition. It rightfully points out that next to technical barriers, important institutional and socio-technical obstacles must be overcome as well. Such obstacles are not only the result from consumer resistance against new technologies, but, and more seriously so, also from current stakeholders' interests to keep in place the existing infrastructure. Especially the automotive industry might show a strong resistance against the large scale adoption of EVs.

Distribution grid impacts of EVs An extensive overview of studies of EV impacts on distribution grid was given in [59] (Gre2011). We do not consider it particularly useful to repeat a large part of the studies mentioned in [59], so below we only discuss a few of the most important EV grid impact papers.

One of the most cited articles on distribution grid impacts of EVs is [44] (Cle2010), which compares a quadratic and dynamic programming approach to study EV impacts (primarily voltage deviations and power losses) on a distribution feeder. Both deterministic and stochastic optimizations are proposed and used in an example case study to minimize the energy losses and voltage deviations. The PhD thesis of the same author extends the analysis to cover a broader range of aspects [60].

[55] presents a conceptual framework for EV integration into power systems (this part was discussed earlier in this section) and additionally studies both a static distribution grid analysis (main output: voltage deviations) and dynamic behavior (output: system frequency response). Both case studies have an isolated grid as object of study. The distribution grid analysis shows, as expected, that congestion and/or unacceptable voltage deviation occurs in the uncontrolled (the authors refer to it as 'dumb charging') charging scenario. Almost all congestion and voltage issues can be managed by applying a smart form of charging, for which in this case no mathematical programming approach was used, but an iterative approach that temporarily halts EV charging in congested lines.

[61] (Tay2010) analyzes a large set of distribution assets in a stochastic way to present probability distributions of asset impacts. An important conclusion in this work is that due to the EV load diversity, i.e. the randomness in the timing of charging EVs leading to a large smoothing of the EV load, especially those assets that have a lower number of customers connected to them are most at risk of being overloaded.

One of the very few studies expressing the impacts of EV charging on distribution networks in monetary terms related to additional investments and energy losses was presented in [62] (Pie2011). In this paper, additional EV related load was imposed on two reference distribution networks, one in rural and one in urban area. Contrary to many studies, the networks are real distribution grids with tens of thousands of consumers connected to them and covering relatively large areas. A large-scale distribution grid planning model was used to asses the required investment in additional grid assets. The results show marked differences between the rural and urban areas. According to the precise EV penetration scenario, the estimated cost savings of moving EV charging to off-peak hours are estimated in the range of 5-35% of the investment costs. Energy losses were found to increase up to 40% due to EV charging.

Co-optimization with respect to balancing power and wholesale prices A number of papers describe how EVs can simultaneously minimize charge costs based on time varying electricity prices and provide minute to minute balancing services. [32] (Rot2010) used a dynamic programming algorithm to find optimal charge schedules that are a balance between charging against low electricity prices and leaving the opportunity to provide regulation services. Indeed it is found that this combination has a higher financial potential than charging solely based on electricity prices. Furthermore, [32] uses a much more complex battery and vehicle model (in driving mode) than many of the EV studies described above.

In [40], [63] and [64] (Sor2011) a variety of optimal EV charging strategies is discussed, among which are combined bidding of ancillary services (two types) and energy purchases, but also load (and energy losses) minimizing strategies. In most of the above papers, the authors refer to their EV charging strategies as *unidirectional V2G*, since no power flows from EV to the grid, but still both regulation up and down can be provided. This should be understood by realizing that lowering the power demand of a group of EVs from, say 200kW to 100kW, is equivalent to delivering 100kW of power when no demand was scheduled. Although the range of regulation power is clearly smaller in this unidirectional approach, there are also important benefits because battery degradation and/or consumer reluctance for this type of service play a less important role.

A true stochastic approach to the combined energy cost minimization and the provision of regulation services was discussed in [65] (Don2012). Here a dynamic programming approach was used to appropriately weigh costs associated with all possible charging trajectories when the EVs are charging and providing regulation services at the same time. A distinct value of the stochastic approach compared to a deterministic method was reported.

EVs in unit commitment One of the first studies to explicitly consider EVs in the unit commitment (UC) problem was described in [66] (Sab2010). In this work, EVs were assumed to have V2G capabilities and, as such, they were modeled as small portable power plants. As far as we can judge based on the description of the paper, however, no details about the driving behavior were taken into account, and only the optimal number of EVs providing V2G services was calculated. We therefore interpret the focus of this paper to be more on the computational method (based on a particle swarm optimization), than on the higher level impacts and benefits from flexible EV demand.

In [67] (Fer2012) EVs with V2G capabilities were included in a UC model of the Spanish power system. A number of scenarios with varying RES and EV penetration were considered. Some of the positive EV impacts that were observed are the reduction of spilled renewable energy, the reduction of the use of pumped hydro storage, fewer hours with high system marginal cost and lower power reserve requirements. Almost of all of these benefits were much greater in the high RES scenario, indicating once more the potential synergy of EVs and RES.

An extension of the work [67] is presented in [68] (Ban2013). Here, too, the effect of including EVs in the UC of the Spanish power system was studied. The model includes a stochastic element by considering wind forecast errors and unplanned thermal unit outages. In addition to an uncontrolled charging profile, three slightly different controlled charging strategies were evaluated: minimizing the total marginal generation costs, maximizing the minimum demand (valley filling) and minimizing spillage of wind generation. The general picture that emerged was similar to that of [67]: controlled EV charging leads to lower generation costs, less hydro pumping and better wind utilization than uncontrolled charging. Results show also that the three different controlled charging strategies lead to very similar outcomes, which could be considered as not surprising since their objectives actually do not differ much. Another noteworthy result is that the EVs could only reduce wind spillage to some extent and a saturation point was observed at some level of EV penetration. Furthermore, although CO_2 emissions per MWh increased in the controlled scenarios due to the increase in cheap coal generation, this effect was offset by the higher hydro pumping losses leading to higher CO_2 emissions in the uncontrolled scenarios.

Another approach to integrating EVs is proposed in [56] and [57]. Here EVs are not explicitly discussed in detail, but they are treated as one form of elastic demand. The idea put forward in the framework proposed in these papers is, contrary to e.g. [66], a distributed and decentralized approach where elastic demand creates and exchanges demand functions by performing optimizations based on a range of price scenarios. In this way, the user preferences and physical constraints of the inelastic demand, are internalized in the demand functions. While this is a promising method as it circumvents the intractable computational problem of a centralized entity scheduling all demand, the inter-temporal constraints[4] of EVs are not treated in detail. These constraints can be a complicating factor, since they create a dependence between the demand functions of different time-steps. This method will also be discussed in chapter 6 of this thesis, where a similar method, but here for the demand function for network capacity, is treated.

3.3 Relative positioning of this thesis regarding the literature

As a means of sketching a coherent picture of the elements of this thesis, we will discuss how, in our opinion, this thesis should be seen relative to the scientific literature on this topic. In chapter 3 we provided an overview of the scientific literature on a research area that can be described as ‘the cross-section of integration of EVs and RES’. In Fig. 3.3 we show the same schematic overview with the chapters of this thesis placed in the diagram. We emphasize that, since we want to elaborate on the contributions of this thesis, we have exaggerated the size of the grey zones denoting the chapters in comparison with the other literature, where a light grey zone denotes a complete ‘sub-field’ and individual author contributions are represented by a point. We do not consider our chapters covering entire ‘sub-fields’ or much broader scopes than other authors.

[4]Inter-temporal constraints have been discussed in chapter 2 regarding generation units. An example in the context of EV charging is that when a battery needs to be fully charged at a certain time-point, this restricts the allowed battery states and thus charging power in previous time-steps.

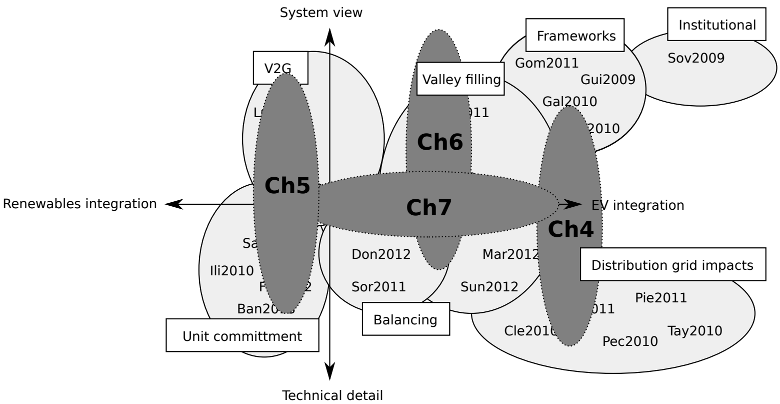


Figure 3.3 – Schematic representation of the elements of this thesis relative to the scientific literature on EVs and renewables integration.

The essence that we aim to express in Fig. 3.3 is that the chapters aim to arrive at system level conclusion from a more technical starting point. The goal in chapters 4, 5 and 6 is not to provide an in-depth technical grid analysis or a new optimization algorithm, but rather to take existing modeling techniques and apply them consequently to one part of the electricity system to arrive at high level system conclusions. This is why indicated the chapters stretching out vertically, hence covering a large part of the y-axis (from technical viewpoint to system view). In chapter 7 the goal was to connect the individual pieces provided by the previous chapters, hence its horizontal shape.

The resulting image could be perceived to bear some resemblance with a sparse-matrix structure. We do not pretend to cover the complete field of renewable and EV integration from technical to system point of view, but rather we studied different aspect stretching between the ends of this field. By this rather wide, though sparse, scope, we hope to have reached conclusions that would have been less obvious when focusing on smaller parts of the scientific field.

Other contributions of this thesis

As explained above, we consider the integrated view that we take, i.e. from distribution grid impacts to EVs supporting renewable energy and the interrelations between these two, one of the core contributions of this thesis since most literature only focuses on single aspects. Secondly, the core chapters themselves have more specific contributions with respect to the state-of-the-art. Below we list the novel research elements that are described in this thesis, in the conclusions sections we list results and new insights that contribute to the state-of-the-art.

- Chapter 4: An EV distribution grid analysis based on *realistic driving patterns and a large number of distribution grids* using realistic and measured grid loads. This allows to quantify system benefits, rather than benefits on an individual (and hypothetical) distribution grid level.

- Chapter 4: A *financial analysis* of EV load induced *distribution asset replacements and energy losses.*
- Chapter 5: Analysis of the *interrelations* between (often seen as alternative technologies of) *smart EV management and cross-border electricity transmission* expansion.
- Chapter 6: Mathematical formulations and analysis of different *congestion management* schemes for aligning *demand response* with *distribution grid* capacity in a *high RES* power system.
- Chapter 7: Analysis of *potential market power* issues by large volumes of *flexible demand.*
- Chapter 7: An exploration of *various sensitivities* related to *demand response.*

Chapter 4

Network impacts and cost savings of controlled EV charging

This chapter has been published as [69] and has its own nomenclature that slightly deviates from the rest of the thesis.

4.1 Introduction

Electric vehicles could be an important contribution to the reduction of greenhouse gases in the transport sector, but concerns have been raised about the impacts of a large fleet of EVs on the electricity distribution grid. A recent overview of studies on different aspects of the impacts was given in [59]. Usually these analyses consider aspects such as energy losses, voltage profiles, reduced lifetime of network components, thermal loadings of cables and transformers, etc. Three fundamental things, however, seem to have received less attention: 1) detailed and realistic charging profiles of EVs based on real life driving data, 2) analyses of the EV impacts on large numbers of operational distribution grids and 3) economic implications of the distribution grid impacts. The work presented in this chapter aims to fill this gap.

Some exceptions regarding the three points above are the work described in [61] and in [70]. In the former study, analyses based on statistics of driving patterns and actual grid assets show that even at low penetrations of EVs, a significant portion of grid assets will be overloaded. Furthermore, it is concluded that controlled charging of EVs can potentially reduce network impacts. The latter study considers an operational distribution grid and shows that controlled charging of EVs can lead to reduced investments in network reinforcements, but the analysis was done for only one grid.

The study presented in this chapter introduces a method to investigate the impacts and economic consequences of EV charging on distribution grids by means of extensive analyses of large datasets of distribution grids and transportation data.

The main emphasis is on comparing controlled and uncontrolled charging scenarios. By considering a large number of distribution grids and different grid assets, we acknowledge the diversity between networks and we aim to point out where impacts are most severe. Furthermore, this approach allows us to quantify the economic impacts on a system level, rather than on the individual network level. Especially for distribution system operators (DSOs) that often operate in a regulated environment, the economic viability of smart grids is a crucial aspect [71].

Our study uses Dutch grid and transportation data, but the methods and most results are more generally applicable. This study partly builds on, but also extends the work presented in [72], which is summarized in appendix B. Whereas in the latter, the emphasis was on the low voltage (LV) part of distribution networks, here we extend the analysis to the medium voltage (MV) parts of the distribution networks and we add economic figures to it. Moreover, our analysis contributes to the broader research topic on how smart grids can lead to more efficient use of electricity grids. Although the flexibility of EV charging might be used for a whole range of applications, the focus of this approach is on reducing the peak load of distribution network assets by throttling the charge rate of the EVs.

4.2 Research method

The approach of this study is to consider a large number of networks, rather than investigating a few sample networks in detail. Because of the large number of networks, the construction of the load profiles in all network nodes and the computation of the power flows are handled in an automated procedure. Inherently, some approximations are made that could produce less accurate results for individual networks. The findings of this study should therefore be understood to be mainly applicable to the system level, rather than for individual network components.

The fact that we use an aggregated approach also has some consequences for the data that we use, which should be recent, readily available and covering the largest possible set of networks. We work mainly with the most recent yearly peak load measurements – a method that is in line with current network planning practice.

4.2.1 Distribution networks

The typical structure of electricity distribution grids often has a historical path dependency and as a result differs from country to country and often even from region to region or town to town. Usually there are also differences between rural and urban regions. We investigate in this chapter a large number of distribution grids in the Netherlands operated by Enexis, one of the largest DSOs in the Netherlands.

The typical structure of electricity distribution grids in the Netherlands is shown in Fig. 4.1. The distribution grids extend from the HV/MV transformer station to the individual household connection. We consider in this chapter four levels of the grid: the HV/MV transformers, the MV transmission cables, the MV distribution cables and the MV/LV transformers. Some essential features of the Dutch distribution networks should be emphasized, because they can differ strongly from distri-

Table 4.1 – Overview of the network data that has been used

Data Type	Number of Records	Relevant Known/Measured properties	Comments
MV/LV Transformers	12.000	Measured yearly maximum power S, nominal capacity, zip code, transformer type properties	Number of households is estimated on the basis of average electricity use per zip code.
MV Cables	13.000 km	Measured yearly maximum power S, cable type properties, connected transformers	The imbalance between the sum of all maximum transformer loads and the maximum of the cable load is corrected for by a coincidence factor and/or fictitious loads.
HV/MV Substations	55 (150 Transformers)	Measured yearly maximum power S, transformer type properties, connected cables	Coincidence factor and/or fictitious load accounts for imbalances.

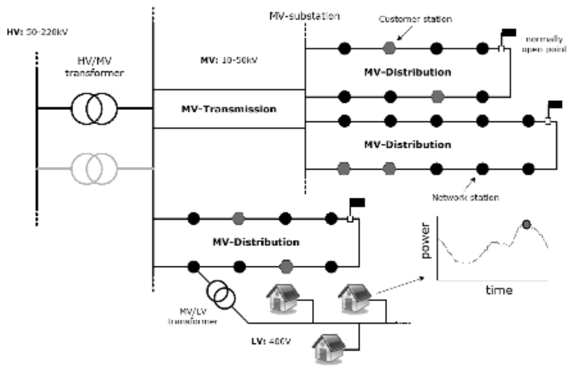


Figure 4.1 – Typical structure of distribution networks in the Netherlands. Picture from [73].

bution networks in other countries. Almost all MV and LV cables are underground cables, which is different from many countries in the world.[1] The typical number of households connected to one MV/LV transformer is 80 and the typical amount of MV/LV transformers connected to one MV distribution cable is 10. Finally, we make a distinction between MV distribution (MV-D) and MV transmission (MV-T) cables. MV-T cables form the connection between the HV/MV substation and the MV distribution station, without any loads (or MV/LV transformers) connected to them. Sometimes the distinction between MV-D and MV-T cables is somewhat arbitrary, when for example the first part of an MV-D cable functions as the MV-T cable to cover a reasonable distance, but at some point of the cable there are loads or transformers connected to it.

[1]This matters especially for the cost calculations since overhead lines are much cheaper than underground cables. Data reported in [62] show differences in the order of a factor 3 to 5. In [62], the values for underground cables are, on the other hand, much higher than the value of 60 €/m that has been used in this analysis.

Figure 4.2 – Locations of analyzed networks in the Netherlands. Each dot represents a MV/LV transformer.

The networks under consideration in this study are described in Table 4.1. If one defines a distribution grid as everything behind a HV/MV substation (which Fig. 4.1 implicitly does), we consider in total 55 networks that cover a substantial part of the Netherlands, see Fig. 4.2.

4.2.2 New load profiles

The following quantities are used in the procedure to calculate the future load profiles. Bold faced quantities denote time profiles, i.e. a vector with values for each 15 minute interval of a day.

$S_{max}(i, t_0)$	Measured peak demand (apparent power)at transformer i in year t_0
$\mathbf{S}(i, t)$	Demand (apparent power) profile at transformer i in year t
$\mathbf{S}_{EV}$	Aggregated EV demand profile normalized to a single EV
$\mathbf{S}_{house}$	Aggregated household demand profile normalized to a single household
$\mathbf{S}_{EVs}(i, t)$	EV demand profile at transformer i, year t
$\mathbf{S}_{houses}(i, t)$	Household demand profile at transformer i, year t
$N_{houses}(i)$	Number of houses connected to transformer i
$N_{Evs}(i, t)$	Number of EVs connected to transformer i in year t
$f(t)$	Fraction of EVs of the total passenger car fleet in year t

The idea is to change the loads of the smallest building blocks (the MV/LV transformers) based upon an estimate of the growth of the household load plus the new EV part. The starting point of the future load profiles is the most recent measured peak demand per transformer (2010 in our case) $S_{max}(i, t_0)$. To obtain a household demand *profile* $\mathbf{S}_{houses}(i, t)$ it is assumed that the transformer load follows a standard household load profile $\mathbf{S}_{house}$ that is used extensively for network planning purposes in the Netherlands [22].

In principle, $\mathbf{S}_{house}$ is defined for each quarter of an hour of the year, but since we are interested in the worst case scenario, we only consider the day with the highest network load. We assume furthermore that the transformer load $\mathbf{S}_{houses}(i, t)$ will grow exponentially with a rate of $a = 1\%$ per year and the shape of the profile does not change, so the time evolution of the demand profile without the EVs for transformer i will be as follows:

$$\mathbf{S}_{houses}(i, t) = S_{max}(i, t_0) \cdot \frac{\mathbf{S}_{house}}{\max\{\mathbf{S}_{house}\}} \cdot (1 + a)^{t-t_0} \tag{4.1}$$

It is emphasized that, strictly speaking, $\mathbf{S}_{houses}(i, t)$ does not necessarily contain only household electricity demand, but also load from public lighting, small stores etc. The name is chosen to distinguish it from the EV load.

To calculate the future EV demand profiles $\mathbf{S}_{EVs}(i, t)$, we use additional information on the amount of expected EVs per transformer and information about driving patterns. For the introduction speed of EVs, an S-curve scenario $f(t)$ as envisioned by the Dutch government is assumed, which saturates at approximately 75% EVs (out of all passenger cars) in 2040 [14]. The electricity demand profile of the EVs will depend on how the EVs are being charged. In this study we consider the different scenarios as presented in [28], where different EV charge profiles $\mathbf{S}_{EV}$ have been derived on the basis of a large dataset of driving patterns in the Netherlands [29]. The fundamental assumptions made to derive the different EV charging profiles are that driving patterns (trip lengths, arrival times, etc) will not change with respect to today and charging is done only at home, after the last arrival of the day. Fig. 4.3 shows the different $\mathbf{S}_{EV}$ profiles added to the standard household profile $\mathbf{S}_{house}$. As Fig. 4.3 illustrates, the controlled charging scenario was derived in such a way that the bulk of the EV load is shifted to the night hours, when network load is low. In this control strategy two objectives are met: 1) the combined peak load of household demand and EV demand is minimal 2) the energy losses are minimal. One could imagine many different control strategies in a smart grid setting, but here the point of view of the distribution network operator is chosen. In a regulated environment, DSOs will generally aim at minimizing costs associated with reinforcing existing grid assets and energy losses. In the remainder of this chapter we will furthermore assume that any IT technology needed for controlled charging of EVs is in place and we will not include its costs in our analysis.

The profiles $\mathbf{S}_{EV}$ represent the aggregate demand of a large number of EVs, but they are normalized to a level of a single EV, so they should be multiplied with the appropriate number of EVs to obtain the correct demand profile $\mathbf{S}_{EV}$ in kVA. To predict the evolution of number of EVs per transformer, the number of houses connected to the transformer is needed. This number, denoted by $N_{houses}(i)$, is either

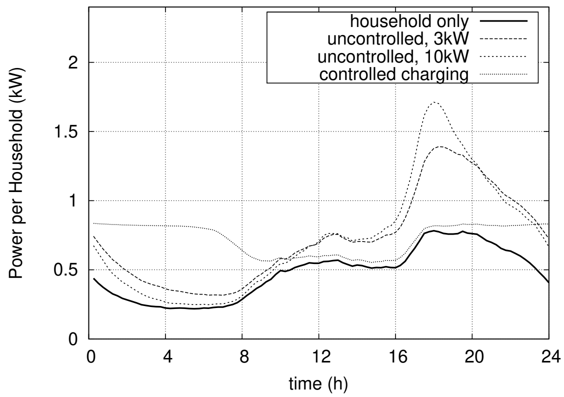


Figure 4.3 – Aggregated demand profiles of household with EV (normalized to one household)

known or else it is estimated by dividing the measured peak at the transformer by the peak value of the standard profile of one household. The estimate will generally be larger than the actual number, due to the fact that we have ignored other loads connected to the transformer such as public lighting, elevators in apartment buildings, etc. To correct for this, the estimate is multiplied by a correction factor so that the average number of estimated households per transformer is equal to the known average actual number of households per transformer. This implies that our estimate of $N_{houses}(i)$ could be less accurate for a single transformer, or even MV cable with a number of transformers connected to it, but the overall picture will be accurate.

The number of EVs connected to transformer i in year t is the product of the penetration rate $f(t)$ and $N_{houses}(i)$, where the fact that the average number of cars per household is one has also been used. So the evolution of the EV demand profile takes the following form:

$$\mathbf{S}_{EVs}(i,t) = N_{EVs}(i,t) \cdot \mathbf{S}_{EV} \tag{4.2}$$

Although not explicitly indicated in Eq. 4.2, we take into account that people in rural areas generally drive larger distances per day, so the magnitude of $\mathbf{S}_{EV}$ depends on the location of the transformer. The zip code that is known for each transformer allows us to connect it with other databases from which we retrieve information in housing density, a measure how rural an area is.

The combined demand profile at transformer i in year t is thus given by:

$$\begin{aligned}\mathbf{S}(i,t) &= \mathbf{S}_{houses}(i,t) + \mathbf{S}_{EVs}(i,t) \\ &= S_{max}(i,t_0) \cdot \frac{\mathbf{S}_{house}}{\max\{\mathbf{S}_{house}\}} \cdot (1+a)^{t-t_0} + N_{EVs}(i,t) \cdot \mathbf{S}_{EV}\end{aligned} \tag{4.3}$$

where the addition of $\mathbf{S}_{houses}(i,t)$ and $\mathbf{S}_{EVs}(i,t)$ is the addition of the P and Q components of S. As an illustration of how fast the peak load grows, Fig. 4.4 shows

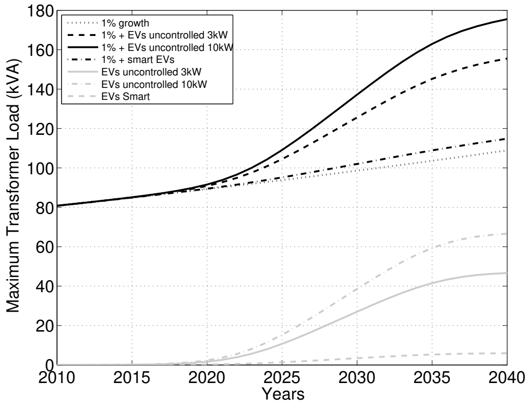


Figure 4.4 – Maximum transformer load in different scenarios of a transformer with 100 houses connected to it

the evolution of the demand peak of a transformer with 100 houses connected to it. In the uncontrolled EV charging scenarios, the EV load is a substantial part of the total load. The profiles of the cable and HV/MV substation loadings are not specified, but follow from the power flow analysis. Fig. 4.5 summarizes the procedure to calculate the future load profiles that have been described in this section.

4.2.3 Power flow

The power flows in the networks have been determined with the commercial package Vision [74], which uses the Newton-Rhapson method to solve the power flow equations. This package is widely used for network planning in the Netherlands, and an important advantage is that the networks we consider are already represented in full detail in the proper format. This means that the most recent measurements of transformer and cable loadings are processed in the Vision network files and the networks are ‘calibrated’ to account for the coincidence factors of loads, non-measured loads and losses. To simulate the new loads, the measured transformer loads are replaced by the new values dictated by Eq. 4.3. The new EV loads are modeled as constant power loads with a power factor of one. These assumptions are in line with the models this DSO uses for network planning purposes and with how the loads are already characterized in the network files.

The output consists of node voltages, line currents, transformer loadings and peak losses in both lines and transformers, which have been calculated using the new load profiles as in Fig. 4.3. The network status is always assumed to be as in normal operation mode, i.e. with network openings (see Fig. 4.1) in open mode. Although node voltages are readily available from the output of the power flow analysis, we will not present them in this chapter. One of the reasons is that unacceptable voltage excursions do not necessarily lead to extra costs, because transformer settings can possibly be changed. Other network impacts such as unsymmetrical loads and

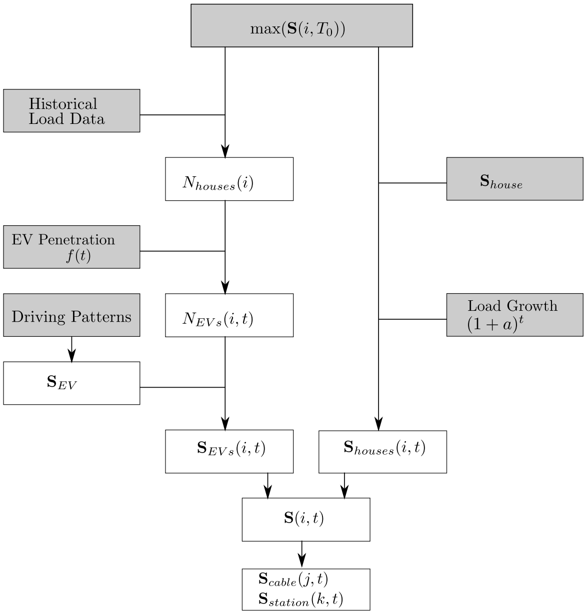


Figure 4.5 – Block diagram illustrating the procedure to obtain the future load profiles $\mathbf{S}(i,t)$, $\mathbf{S}_{cable}(j,t)$ and $\mathbf{S}_{station}(k,t)$. Quantities in grey blocks are input data, white blocks denoted calculated values.

harmonics have also been discarded.

We emphasize that only the values of the MV/LV transformers have been changed and the new peak loads in all network parts higher than the MV/LV transformers follow directly from the power flow simulations. In general, the relative increase in peak load due to the EVs will be lower for the higher network levels, since the relative share of the residential load is lower due to the presence of commercial and industrial consumers.

4.2.4 Energy loss estimation

The following quantities will be used in the next two sections to calculate the energy losses and various economic figures. Note that index i is now used to denote any component including cables and HV/MV transformers.

$\mathbf{S}(i,t)$	Demand (apparent power) profile at *component* i in year t
$t_{ol}(i)$	Year component i will be overloaded
$T_{L,peak}(i,t)$	Service time of the peak loss at component i in year t
$T_{L,0}(i)$	Service time of component i
$P_{L,peak}(i)$	Peak loss of component i
$P_{L,0}(i)$	No load loss of component i
$S_{nom}(i)$	Nominal thermal capacity of component i
$AC_{rpl}(i,t)$	Annuity charges of component i in year t

$C_{asset}(i)$	Asset costs of component i
$C_{loss}(i,t)$	Loss costs of component i in year t
$C_{total}(t)$	Total costs in year t
NPV	Net present value

For network planning purposes, energy losses in different network assets are usually estimated based on information that is readily available for the DSO: yearly peak loading of the network assets [75]. The yearly losses can then be estimated with the help of the asset properties (including the distribution of loads along a cable) and an assumed yearly load profile. The commercial power flow solver used in this study uses the asset properties and peak load values to calculate the peak loss $P_{loss,peak}$ and the no-load loss $P_{loss,0}$. These numbers can be converted to the yearly energy losses by invoking the service time of the peak loss T_L , which contain information of the shape of the load profile and the standard service time of transformers T_0 (see e.g. [75] and [73]). For a transformer the yearly energy losses are then given by:

$$E_{loss}(i,t) = \alpha^2(i,t)P_{L,peak}(i)T_L(i,t) + P_{L,0}(i)T_0 \tag{4.4}$$

and for a cable

$$E_{loss}(i,t) = \alpha^2(i,t)P_{L,peak}(i)T_L(i,t) \tag{4.5}$$

where $\alpha(i,t) = \frac{\max\{\mathbf{S}(i,t)\}}{S_{nom}(i)}$ is the utilization factor of the asset and $T_0 = 8760$h. Load independent losses, also referred to as *iron-losses* are mainly present in transformers and are associated with phenomena such as eddy currents and hysteresis effects, which depend on frequency and/or voltage. Here, they are assumed to be constant for one type of asset.

The evolution over time of the losses is then determined by the product of the evolution of the service time of peak loss and the utilization factor. These are known exactly for the MV/LV transformers (since they are dictated by the load growth and EV profile), and for the higher network levels they follow from the relative sizes of the residential and industrial/commercial loads. The time dependence of $P_{loss,peak}$ and $P_{loss,0}$ has not been stated explicit in Eqs. 4.4 and 4.5, because it is assumed constant for one type of asset. However, when in our cost analysis overloaded assets are replaced, the values of $P_{loss,peak}$ and $P_{loss,0}$ change accordingly. Usually the load dependent losses will be lower for a higher capacity asset (at the same transported power), because Ohmic resistance is reduced. Alternatively, the load independent iron losses of transformers could increase slightly after replacement, this depends on the exact type of transformer. As an example, Fig. 4.6 shows the evolution of the yearly energy losses of one specific transformer whose threshold value is exceeded after some years in the case of the uncontrolled charging scenarios. The 20-25 % reduction in energy losses due to the replacement are clearly visible. It will depend per asset if the overall losses over the 30 year horizon end up lower or higher in the controlled or uncontrolled scenario; in the example of Fig. 4.6 the integral over the losses is similar for the controlled and uncontrolled cases.

It should also be emphasized that we consider no loss minimization by controlling node voltages and/or reactive power injections. Although this could clearly be an interesting application in future smart grids, we consider this outside the scope of this study.

4.2.5 Costs

We calculate expected differences in costs between the EV charging scenarios by considering replacement costs if an overloaded asset has to be replaced and the energy loss costs. In our model, an asset is replaced by a type with a higher capacity in the year the threshold value defined in Table 4.3 is exceeded, so the investment (or cash flow CF) due to the replacement of component i in year t is given by:

$$CF_{rpl}(i,t) = \begin{cases} C_{asset}(i) & \text{if } t = t_{ol}(i) \\ 0 & \text{else} \end{cases} \tag{4.6}$$

For the replacement costs, we take the *annuity charges* associated with the investment in new assets. The annuity charges can be considered to represent the yearly amount that, over the life of the asset, has a net present value exactly equal to the asset's initial cost:

$$AC_{rpl}(i,t) = \begin{cases} C_{asset}(i) \cdot & \dfrac{r}{1-(1+r)^{-T_{life}(i)}} \\ & \text{if } t_{ol}(i) \leq t < t_{ol}(i) + T_{life}(i) \\ 0 & \text{else} \end{cases} \tag{4.7}$$

where $r = 3\%$ is the interest rate based on the current value of Dutch treasury bonds and the expected lifetimes are 50 years for MV/LV transformers and cables and 40 years for HV/MV transformers.

The asset costs $C_{asset}(i)$ incorporate all possible costs associated with a replacement: material, labor, taxes, etc. In general, reinforcement of a certain network component can be done in various ways, but we assume a straightforward replacement by a heavier type of the same component. Cables are replaced by a higher capacity type over the entire cable segment that was overloaded. It is stressed that we focus only on the reinforcement of *existing* networks, thereby neglecting costs associated with the construction of completely new networks. The values of the asset costs are assumed to be constant over time and they are based on figures that are currently being used for network planning purposes at the DSO controlling the networks that this study considers and are given in Table 4.2.

The costs of energy losses for component i in year t are given by

$$C_{loss}(i,t) = E_{loss}(i,t)C_{el} \tag{4.8}$$

where C_{el} denotes the electricity price, which is based on average Dutch electricity prices and we assume it to be constant.

Total yearly costs are found by summing up replacement annuity charges and energy loss costs of all network components:

$$C_{total}(t) = \sum_{i=1}^{N} (AC_{rpl}(i,t) + C_{loss}(i,t)) \tag{4.9}$$

Table 4.2 – Asset costs and energy loss costs. The asset costs differ from asset to asset; values in this table are typical values.

Cost Type	Price
MV/LV Transformer	10.000 €
MV Cable	60 €/m
HV/MV Substation	1.200.000 €
Energy Loss	0.06 €/kWh

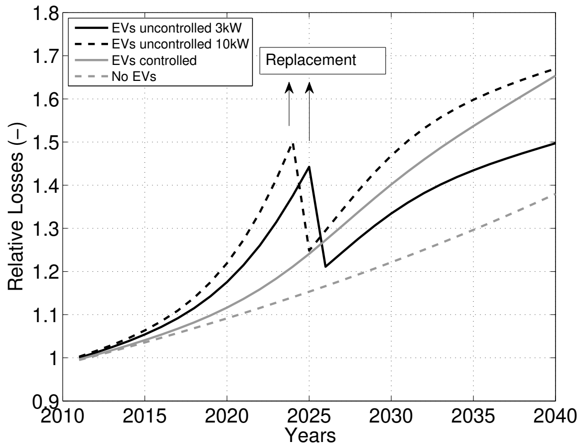


Figure 4.6 – Time evolution of the losses in one of the MV/LV transformers for the different scenarios. Losses are reduced when the transformer is replaced by a type with higher capacity.

Eq. 4.9 can be converted to net present value according to:

$$NPV = \sum_{t=t_0}^{t_f} \frac{C_{total}(t)}{(1+r)^{t-t_0}} \quad (4.10)$$

where $t_f = 2040$ in our case. The fact that our time-horizon lies at the year 2040 means that a significant portion of the replacement costs as defined by 4.7 fall outside the scope of this analysis. Also, unrecoverable sunk costs resulting from assets being replaced before the end of their economic lifetime are not taken into account. These notions should be taken into consideration when interpreting the results.

Fig. 4.7 schematically summarizes the procedure to calculate expected costs that has been described in this section.

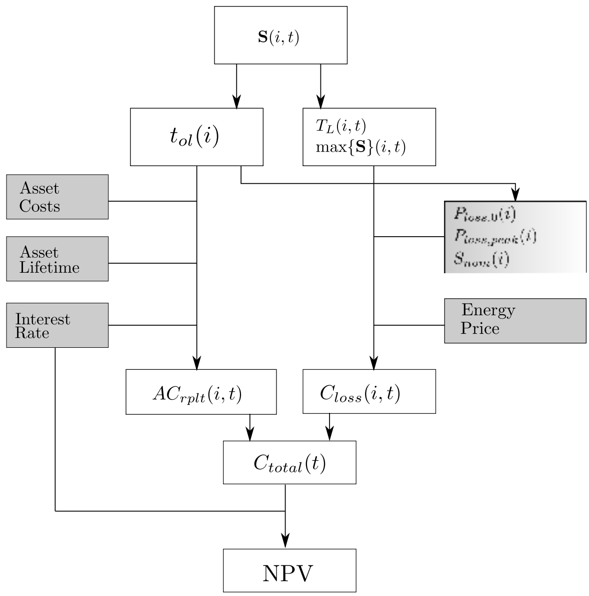


Figure 4.7 – Block diagram illustrating the procedure to calculate the total costs.

4.3 Results

4.3.1 MV/LV Transformers

Fig. 4.8 shows histograms of expected MV/LV transformer loadings in the three EV charging scenarios, together with the scenario of 1% growth only. The figures also denote the percentage of overloaded transformers, for an overload criterion of 1.16. This value reflects the fact that we are considering an instantaneous peak value, which can be higher than the nameplate capacity for some time. The number of overloaded transformers can be interpreted as the fraction of transformers that would have to be replaced. The data represents a subset of only those transformers connected to residential customers, i.e. transformers connected to large industrial or commercial customers have been omitted. The effect of the control of the EV charging is pronounced: the amount of overload transformers that would have had to be replaced decreases substantially. Compared to the situation with no EVs (the thin black line in the histograms of Fig. 4.8), there are hardly any extra replacements needed.

4.3.2 MV cables

Fig. 4.9(a) shows the distribution of the loadings of MV distribution (MV-D) cables in the uncontrolled 3kW scenario and the controlled scenario. The histograms of the other scenarios are not shown anymore, because their shape will resemble the ones presented here. The overload criterion has been set to 60% of the nominal value of the current in the cable. This reflects the fact that typically the MV-D cables are

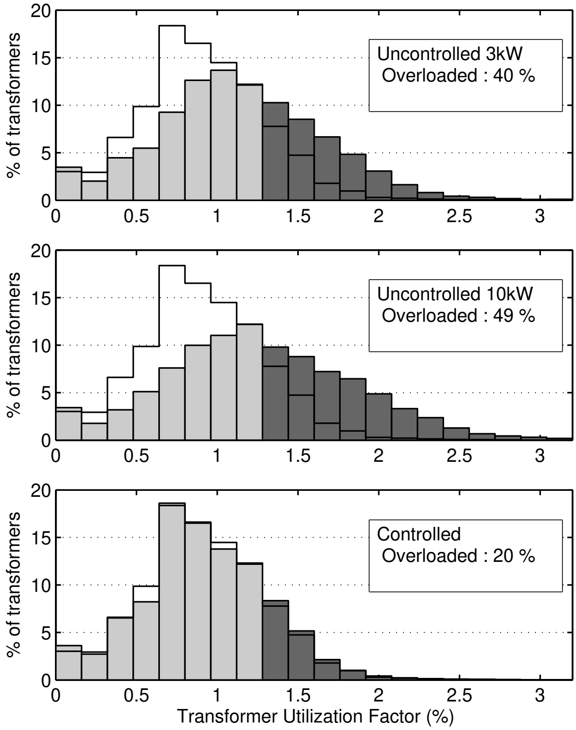
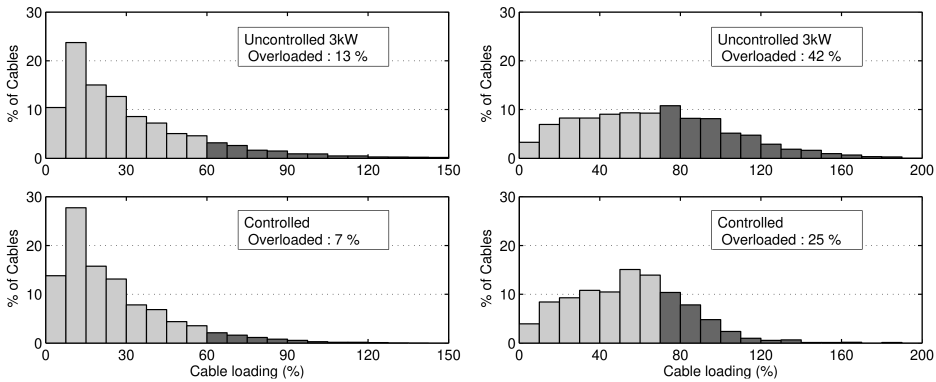


Figure 4.8 – Distribution of MV/LV transformer loadings. The thin black line behind the histogram bars denotes the situation with 1 % growth without EVs. The color change in the histogram bars denote the values where the threshold value has been exceeded.



(a) MV distribution cables (b) MV transmission cables

Figure 4.9 – Distribution of MV cable loadings.

laid out in a ring structure (see Fig. 4.1) and in case of a fault somewhere in the ring, the net opening will be closed and the cable on one side of the ring has to serve the entire ring to comply with the N-1 criterion.[2] In such mode of operation, cable loadings up to 120% are tolerable for some time.

It can be seen that the number of overloaded MV-D cables is much lower than number of overloaded MV/LV transformers. This leads to the conclusion that there is much more 'room'for extra load on the MV distribution cables than on the transformers. A possible explanation for this observation is the following, which is a result of our method of bookkeeping: in a typical MV distribution ring as depicted in Fig. 4.1, the cable segments between the MV/LV transformers are counted as separate cables. It is then likely that the last segments of the cables have a much lower load because they are effectively serving only one or even no transformer at all in normal operation. One could speculate, however, that the differences are also the result of the fact that due to much higher labour costs of installing a new MV cable (since they generally are underground cables), DSOs have typically installed cables with much higher capacity to avoid costly reinforcement, which involves digging along the entire length of the old cable.

Fig. 4.9(b) shows the expected loadings of the MV transmission (MV-T) cables. Here, the overload criterion is 68% of nominal value rather than 60% in the case of MV-D cables. This reflects the fact that usually there are two or more parallel MV-T cables, that serve as backup to comply with N-1 standards, see [73] for more details. Most notably, the amount of overloaded cables is much higher in all scenarios than in the case with MV-D cables. Apparently, the MV-T cables have much less spare capacity, which is expected since they transfer the power for an entire MV distribution ring. It should be noted that if one considers the distributions of all MV cables, they strongly resemble the distributions of the MV-D cables, since there are far less MV-T cables.

[2]The N-1 reliability criterion states, loosely speaking, that all loads should still be served after failure of one asset.

Table 4.3 – Overview of the fraction of transformers/cables whose threshold value has been exceeded for the different charging scenarios. The values denote the situation in 2040 with roughly 75% of all households owning an EV.

Property	Threshold	No EVs	Unc.3kW	Unc.10kW	Cont.
MV/LV Transformers	1.16	18%	40%	49%	20%
MV Distribution Cables	0.6	6%	13%	15%	7%
MV Transmission Cables	0.68	22%	42%	46%	25%
HV/MV substations	varies	35%	61%	66%	42%

In both the MV-D and the MV-T cables, the effect of applying the EV charge control is imminent: much fewer overloaded cables in the controlled scenario. It will be clear that this could lead to a dramatic reduction in investment costs that would be needed to accommodate new EV loads and/or growth of the household electricity demand.

4.3.3 HV/MV substations

Fig. 4.10 shows the distribution of the loading of the HV/MV substations in the different EV charging scenarios. The overloading criterion depends on the configuration of the specific substation by taking into account the N-1 criterion and has been determined for each substation individually. Usually there are a number of actual transformers in one substation, so if for example the substation has three 40MVA transformers, the overload criterion is 80MVA, because that is the highest load than can be supplied by two of the three transformers. In the Fig. 4.10 a utilization factor of one hence denotes the safe N-1 capacity of the substation. The amount of overloadings is clearly highest for the HV/MV substations compared to any other types of grid asset we considered. A possible explanation for this could the fact that, since a HV/MV transformer requires by far the highest cost to install (or replace) and its costs are dominated by material rather than labor costs, DSOs usually choose not to build much extra capacity. A new transformer is only installed in a substation when the safe N-1 capacity threatens to be exceeded. This also implies that a substation that is counted as overloaded does not have to be replaced altogether, but its capacity can be enhanced by installing another transformer with accompanying switchgear. The most important results in terms of asset overloadings are summarized in table 4.3.

4.3.4 Economic figures

Table 4.4 shows the NPV for all the scenarios compared to the baseline scenario without EVs but with a yearly 1% load growth. The potential cost savings for controlled charging of EVs are around 20 % compared to the uncontrolled scenarios. It is emphasized that the absolute numbers are somewhat arbitrary because they only represent a part of the networks in a part of the Netherlands. It can be seen that the energy loss costs dominate the total figures. It should be realized, however, that

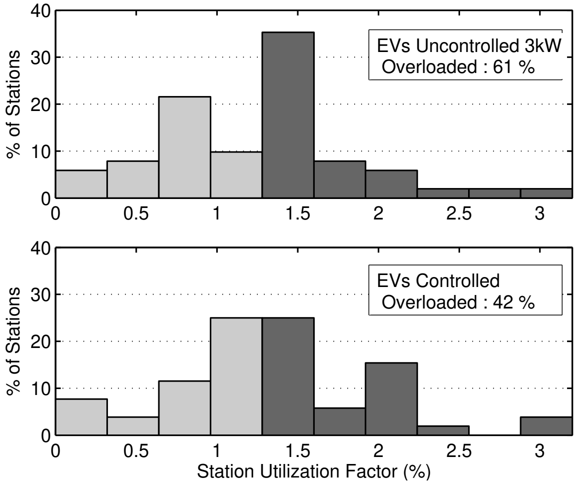


Figure 4.10 – Distribution of HV/MV transformer station loadings

this can partly be explained by the fact that the replacement costs are spread over a large period which lies largely outside the time-horizon. Although in the NPV figures the replacement costs are dwarfed by the energy loss costs, the *differences* between the scenarios are distributed more evenly across the various cost components. Since we are interested in the potential cost savings due to controlling the EV charging process, we discuss this point further by comparing the controlled and the uncontrolled 3kW scenario. From Table 4.4 it can be deduced that the cost savings in the controlled scenario are approximately 60% due to lower replacement costs and 40% due to lower energy losses. Fig. 4.12 shows specifically what components are responsible for the difference in costs between the uncontrolled 3kW and the controlled scenario. The cable replacements and cable losses are the main cause for the cost difference. Transformer losses, replacements and station replacements are similar in size. Station losses actually have a slightly negative contribution: they are higher in the uncontrolled scenario due to the replacements which lower the energy losses.

To get some insight in the pattern of required investments, Fig. 4.13 shows the annual cash flows defined by Eqs. 4.6 and 4.8 for the different cost components for the uncontrolled 3kW scenario. Whereas the energy loss costs increase steadily, the investments in replacements show a distinct peak around the year 2025.

Fig. 4.14 shows the total annual cash flows for all the scenarios. The investment peak present in the uncontrolled charging scenarios is absent in the controlled charging scenario. Hence, we can conclude that the replacement cost differences as reflected in Table 4.4 are almost solely caused in the period between 2015 and 2035. It is again emphasized that the annual payments as a result of these replacements (Eq. 4.7) will last much longer.

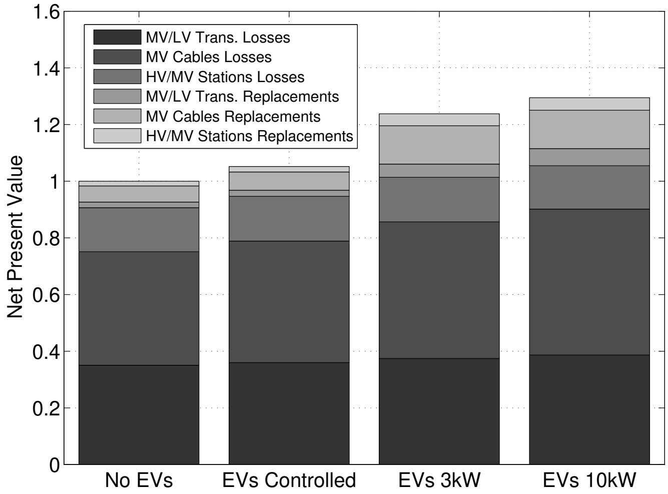


Figure 4.11 – Break-down into different components of the NPV for all scenarios.

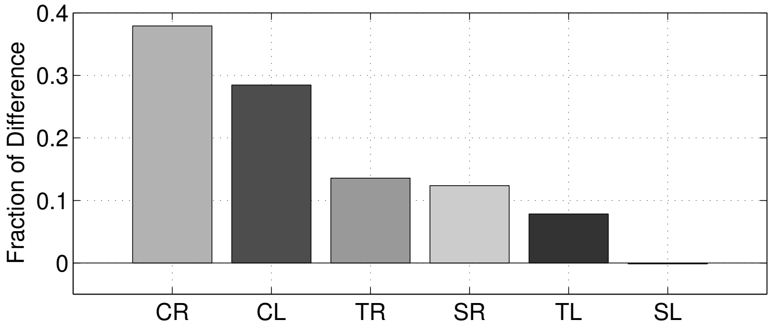


Figure 4.12 – Break-down of the difference in NPV between in the uncontrolled 3kW and the controlled scenario. Colors match with Fig. 4.11. C, T, and S stand for cables, transformers and stations, respectively. L and R stand for losses and replacements.

Table 4.4 – Overview of the net present value (NPV) of the different scenarios compared to the base case scenario without electric vehicles.

Scenario	Total	Replacements	Energy Loss
No EVs (absolute)	265M €	25M €	240M €
No EVs	100 %	100 %	100 %
EVs controlled	105 %	113 %	104 %
EVs uncontr. 3 kW	124 %	240 %	112 %
EVs uncontr. 10 kW	129 %	257 %	116 %

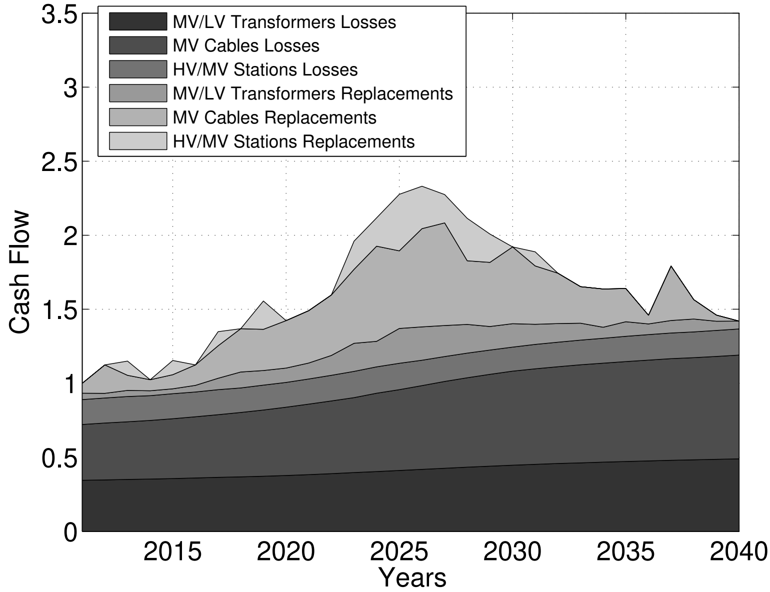


Figure 4.13 – Annual cash flow for different components for the uncontrolled 3 kW scenario. The cash flows are relative to the yearly cash flow in 2010.

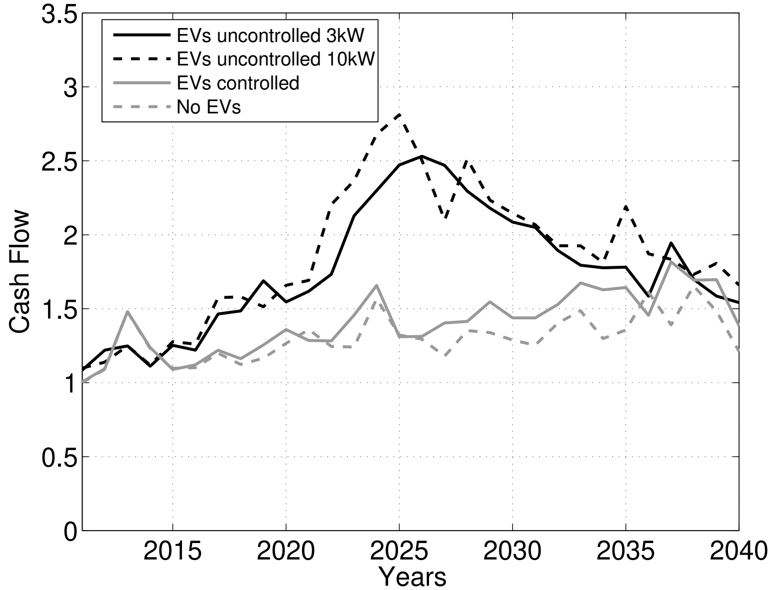


Figure 4.14 – Total (replacements + losses) yearly cash flow for all scenarios.

4.4 Conclusions

A method to assess the network impacts of EV charging and its economic consequences has been presented in this chapter. This approach, that combines recent network load measurements and modeled future EV profiles, has been used to analyze a large number of operational distribution networks and calculate the resulting costs for energy losses and reinforcement of network components. Because our analysis covers a large set of different distribution networks consisting of thousands of different grid assets, our findings should be interpreted to reflect system level figures rather than predictions for individual networks or assets. Within the validity of our assumptions, however, a number of important conclusions can be drawn.

Most importantly, it has been shown that controlled charging of EVs leads to a significant reduction of overloaded network components compared to the uncontrolled charging scenarios. There are, however, marked differences between the impacts on various parts of the networks. The most severe impact, in terms of percentage of overloaded components, is to be expected on the HV/MV transformer station level, followed by MV/LV transformers and MV cables. Regarding the MV cables, the effects on MV transmission cables are more severe than on the MV distribution cables.

The economic analysis shows that the expected NPV of all network reinforcements and energy losses differs approximately 20% between the uncontrolled and controlled charging scenarios. The cost savings due to controlled charging are most pronounced on the MV cable level. Furthermore, the energy loss costs were found to be the most important component of the NPV and they were found to differ only moderately between the controlled and uncontrolled charging scenarios. The *differences* in costs between the controlled and uncontrolled scenarios, however, are approximately 60% due to reduced investment costs and 40% due to lower energy losses.

The implications of these results for DSOs are not straightforward and depend largely on the institutional setting the DSO is operating in. One could argue that the results presented in this study give a strong indication that there is a societal benefit in allowing DSOs to apply some form of charge control – something that is not allowed in many regulated electricity sectors. In a regulated environment where DSOs compete through yardstick price regulation, this study furthermore suggests that if an EV penetration scenario like the one considered in this chapter materializes, DSOs should anticipate a period with distinctly higher investment levels.

A number of venues for future research can be identified from this chapter. A logical step to take would be to assess other types of network impacts such as voltage excursions, reduced lifetimes of components, harmonics, unsymmetrical loads, etc. In principle, the same method to derive the future load profiles can be applied for these and other types of network impacts, although additional information will be required. It would also be interesting to asses the network impacts of charge profiles that result from different optimization objectives. For example, a situation where EVs are used for frequency regulation might lead to completely different profiles with possibly much higher peaks in the network. In addition to this, a stochastic approach could provide more insights into *probabilities* of certain network impacts.

The economic analyses have shown that although the reduction of the amount of assets replacements due to controlling the charge process is significant, the resulting difference in NPV is quite moderate. This demonstrates that it is not easy to capture the costs of EV charging in a single number. One could argue that this is partly due to the fact that such costs are not only the result of events happening in the period under consideration, but also from the current state of the network - a result of decisions in the past - and future developments that lie far beyond the end of the considered period. It would be interesting to see if an economic analyses that uses more detailed financial data and accounting methods on the individual asset level, would produce different insights. One could speculate that such insights could lead to a shift in optimization objectives that a DSO aims to fulfill with the control of EV charging or with regard to grid expansion strategies.

The policy implications of this study are not straightforward and offer another possibility for future research. Nevertheless, despite the fact that we have only focused on a single aspect of the broad concept of smart grids, our study strengthens the confidence that the deployment of an information and communication infrastructure to enable more flexible and intelligent electricity grids is worthwhile.

Chapter 5

Impacts of controlled EV charging on cross-border electricity flows

This chapter is based on [76]

5.1 Introduction

The continuing growth of the share of renewable energy sources (RES) increasingly poses a challenge to the traditional operation of the power system. In particular the intermittent character of wind and solar PV generation, combined with wind and irradiation forecast uncertainties, poses a tough problem that could hamper the integration of RES. A few, possibly complementary, solution approaches are often proposed in this context, see e.g. [77]: a large enough interconnected grid to smoothen out fluctuations in renewable energy production, large-scale electricity storage, (fossil fuel fired) back-up plants, and responsive demand of electricity. Essentially these options fall in two main solution approaches: inter-temporal vs. inter-locational arbitrage.

Large-scale hydro storage options are not economically available everywhere while thermal back-up plants are costly and polluting. Regarding the option of demand response, electric vehicles (EVs) are a good candidate to fulfill an important role as flexible loads, because typical EV battery sizes and daily driving distance usually allow the charging process to be controlled and/or postponed for a few hours up to several days. Because of this potentially large source of flexible electricity demand, controlled charging of EVs has received much attention lately in a variety of different contexts [50]. The natural combination of RES and EVs was first described extensively in [42] and was further explored in e.g. [46]. Other work has focused on relieving distribution network impacts (see e.g. [59]), using EVs for balancing purposes (or other ancillary services) [78], EVs reacting on anticipated day-ahead electricity prices (e.g. [39]) but also in unit commitment models [66].

The other category of approaches to ease the integration of RES focuses on increased interconnection capacity between different power systems. A number of studies have reported on how large interconnected power systems help to smoothen out the variable production profiles of wind and PV. In the European context an important contribution was given by [79]. In this report, it was shown how very high RES penetration together with heavily increased interconnection capacity has the potential to almost complete curb carbon emissions of the electricity sector. Although the focus was on cross-border transmission, it was also acknowledged that demand response could play a key role in dealing with variability of renewables.

Other studies were carried out more from a perspective of meteorological time-series, and it was shown in e.g. [80] and [81] that even with an infinite-capacity transmission network, a very large storage capacity or back up generation to cover periods with low wind and sun are still needed, mainly in winter periods with blocking high pressure systems over Europe. In [82], a European grid model and future (renewable) generation capacities scenarios have been used to show how cross-border electricity flows will change. The general picture that emerges from these studies is that, indeed, interconnection of power systems can play an important role in a sustainable Europe, but the cross-border transmission capacity that is needed is very large, and additional measures may well prove to be a cost-efficient addition to transmission capacity.

Despite the large body of literature related to RES and EV integration issues, a number of things seemed to have received less attention. For example, many of the studies that investigated the relation between EVs and RES have focused on regional or national electricity systems and ignored the dependence of neighboring power systems. The large-scale oriented studies have, on the contrary, often ignored EVs as potential responsive demand. Next to this, many RES integration studies have primarily focused on wind, since the share of solar energy only grew to substantial numbers in the past few years.

The goal of this work is to investigate to what extent controlled charging of EVs and extra transmission capacity are related to each other in systems with a high share of renewable energy production. Intuitively, since they are both forms of arbitrage, the two options are often seen as substitute technologies: increasing the one would lead to a lower value of the other. If they were complements, they would actually strengthen each other. Hence, this study aims to shed more light into the question to what extent EV control impacts the needs for cross-border transmission. We do so by using a unit commitment model where the EV charging is explicitly taken into account as decision variable. We then apply our model to a case study of a conceptual two-node system in order to get qualitative insights in dispatch profiles, generation costs and transmission needs. We aim to identify relevant conditions that influence the extent of substitution between the two technologies and we explore sensitivities of the results to various parameters. A second case study using the same model is described in more detail in [76] and [83]. This case study focuses on the full European electricity system using realistic transmission and generation portfolio scenarios.

Results of this chapter show that the demand for arbitrage is key in understanding the value of transmission and EV control. Under modest RES and transmission scenarios, EVs and transmission can be seen as partially substitute technologies, although the value of both technologies is mostly independent of the other. However, when RES penetration increases to very high levels, *both* control and transmission become necessary and the two technologies actually become complementary, i.e. the value of both technologies simultaneously is higher than the sum of their values individually.

5.2 Model formulations

In the following section we will describe our least-cost unit commitment model. The EVs are an explicit part of the models, so we will start this section by describing the EV charging model.

5.2.1 EV charging model

To include EVs in the unit commitment model, we need information on the charging needs of the EVs. These are dictated by their driving needs in combination with technical vehicle parameters such as their battery capacity. Currently, the number of EVs on the road is very modest, so we model EV driving patterns based on current driving data which represent gasoline powered vehicles. Hence, the fundamental assumption that we make by using conventional vehicle driving data is that EV driving patterns will be similar to those of conventional gasoline vehicles.

EV charging can be described with a linear state equation that relates the battery state-of-charge (SoC) to the charging power and discharges due to driving. The SoC (expressed in terms of energy) of vehicle i at time-step k is given by

$$E_{EV,ik+1} = E_{EV,ik} + \eta_c P_{EV,ik} - d_{ik} \qquad \forall i,k \tag{5.1}$$

Here η_c represents the charging efficiency and $-d_{ik}$ represents the discharges due to driving. The technical limits of $E_{EV,ik}$ and $P_{EV,ik}$ are denoted by $E_{EV_{min},i}$, $E_{EV_{max},i}$, $P_{EV_{min},i}$ and $P_{EV_{max},i}$. In the remainder of this chapter we assume that vehicles cannot deliver energy back to the grid, hence $P_{EV_{min},i} = 0$. The upper limit $P_{EV_{max},i}$ is either dictated by the grid connection, the inverter limits or even charge acceptance by the battery material. We are, however, not interested in the nature of the limiting factor and assume a constant value for each vehicle.

5.2.2 EV data

The driving data originates from a large mobility survey performed in the Netherlands [29]. This data is also used and described more extensively in [28]. The data provide trip lengths, departure and arrival times, trip durations, trip destinations etc. Furthermore, we assume a constant kWh usage per km driven (0.2 kWh/km), so the discharges due to driving $-d_{ik}$ follow in a straightforward way from the driving data.

We assume the technical vehicle parameters to be $P_{EV_{max},i} = 3$kW, $P_{EV_{min},i} = 0$, $E_{EV_{max},i} = 24$kWh, and we let these vary randomly within 10% of these average values to introduce some differences between the vehicles. Furthermore, we assume lossless charging, hence $\eta_c = 1$ in Eq. 5.1.

5.2.3 Charging scenarios

We will consider two charging scenarios: 1) optimal charging, where $P_{EV,ik}$ is an optimization variable to minimize total generation costs, and 2) uncontrolled charging, where vehicles only charge at home with a constant $P_{EV,ik}$ after the last arrival at home. The uncontrolled charging scenario is described in more detail in [28] and chapter 2 of this thesis. Briefly described, in the uncontrolled charging scenario the charging power is given by $P_{EV,ik} = P_{EV_{max,i}}$ between the moment of the last arrival at home until the battery is fully charged.

For the optimal charging scenario, the time-dependent EV charging power $P_{EV,ik}$ will be an optimization variable in a unit commitment model. Hence, this model finds the right moments to charge the EVs in order to minimize the total electricity generation costs, while still respecting the driving needs of the EVs. The driving data thus enter the unit commitment problem through the d_{ik} term in Eq. 5.1. The smaller this term in comparison with the battery size ($E_{EV_{max},i}$), the less flexibility there is in postponing the moment of charging.

5.2.4 Typical EV fleet

In principle, every single EV can be taken into account in the optimization, but the number of variables would become enormous, so some sort of aggregation to lump many individual EVs in a single one is needed. We divide the EV fleet in 25 typical EVs (since this was computationally tractable), by means of a K-means clustering algorithm that is described in [39] for the same purpose. A small deviation from [39] is that we choose to work with equal cluster sizes, which allows us to simply multiply all the single EV equations with a single scaling factor that represents the ratio of total EVs in the system divided by the amount of EVs in the model. To obtain equal cluster sizes, we use a pragmatic way to redistribute entries in overpopulated clusters to an underpopulated cluster with the closest Euclidean distance from it. This procedure is describe in more detail in appendix D.

Scaling the aggregated vehicle demand to represent national levels is done by invoking the total amount of passenger car vehicles per country given in [84] and we assume an EV penetration of 25%. The largest differences between the vehicles are of course the driving patters (the d_{ik} in 5.1), and as explained above, they follow from the dataset described in [28]. We thus use Dutch data and hereby we assume that the driving *patterns* (except for the distances) do not differ much between countries.

5.2.5 One node unit commitment model

The basic unit commitment model is based on [85], chapter 2.7. We have adapted the model slightly by ignoring reliability constraints and adding pumped hydro equations and renewable energy generators.

$$\underset{P_{G,nk},u_{nk},y_{nk},z_{nk},P_{Hjk}}{\text{minimize}} \sum_{k=1}^{N_k}\sum_{n=1}^{N_G} P_{G,nk}MC_n + y_{nk}SUC_n + z_{nk}SDC_n \tag{5.2}$$

subject to

$$u_{nk}P_{G_{min},n} \leq P_{G,nk} \leq u_{nk}P_{G_{max},n} \qquad \forall n,k \tag{5.3}$$

$$P_{G,nk-1} - P_{G,nk} \leq RD_n \qquad \forall n,k \tag{5.4}$$

$$P_{G,nk} - P_{G,nk-1} \leq RU_n \qquad \forall n,k \tag{5.5}$$

$$y_{nk} - z_{nk} = u_{nk} - u_{nk-1} \qquad \forall n,k \tag{5.6}$$

$$P_{H_{min},j} \leq P_{Hjk} \leq P_{H_{max},j} \qquad \forall j,k \tag{5.7}$$

$$H_{min,j} \leq H_{jk} \leq H_{max,j} \qquad \forall j,k \tag{5.8}$$

$$H_{jk} = \begin{cases} H_{jk-1} + H_{in,jk} + \eta_H P_{Hjk} & \text{if } P_{Hjk} \geq 0 \\ H_{jk-1} + H_{in,jk} + \frac{1}{\eta_H} P_{Hjk} & \text{if } P_{Hjk} < 0 \end{cases} \qquad \forall j,k \tag{5.9}$$

$$\sum_{n=1}^{N_G} P_{G,nk} - \sum_{j=1}^{N_H} P_{Hjk} = P_{D,k} \qquad \forall k \tag{5.10}$$

We give a brief description of the meaning of the equations: the objective function 5.2 represents the costs of all plants N_G and all time-steps N_k and is the sum of marginal costs MC (linear with output P_{nk}) and the start-up SUC and shut-down costs SDC. The binary variables u, y and z represent if a unit n is on-line, in start-up mode and in shut-down mode, respectively. Eq. 5.3 denotes the power limits $P_{min,n}$ and $P_{max,n}$ of the generators. Eqs. 5.4 and 5.5 denote the ramping limits RD (down) and RU (up) of the generators. The start-up and shut-down logic is expressed in Eq. 5.6. The pumped hydro power P_H for all units j (positive for pumping, negative for producing) has limits P_{Hmin} and P_{Hmax}; these are expressed in Eq. 5.7. The hydro reservoir level H has to be within limits H_{min} and H_{max} given by constraint 5.8. The relation between hydro power and reservoir level in Eq. 5.9, where one also observes the inflow term H_{in} . Finally, the load balance equation is given in Eq. 5.10, which says that the sum of generation equals demand P_D. The optimization problem given by Eqs. 5.2 to 5.10 is mixed-integer linear programming problem. It has been programmed in Matlab and solved with the IBM ILOG CPLEX solver [86].

5.2.6 Multi node unit commitment model with flexible EV load

The full model for a multi node systems with controllable EVs reads

$$\underset{P_G,u,y,z,P_H,P_{EV}}{\text{minimize}} \sum_{k=1}^{N_k} \sum_{n=1}^{N_G} P_{G,nk} MC_n + y_{nk} SUC_n + z_{nk} SDC_n \tag{5.11}$$

subject to

$$u_{nk} P_{G_{min},n} \leq P_{G,nk} \leq u_{nk} P_{G_{max},n} \qquad \forall n,k \tag{5.12}$$

$$P_{G,nk-1} - P_{G,nk} \leq RD_n \qquad \forall n,k \tag{5.13}$$

$$P_{G,nk} - P_{G,nk-1} \leq RU_n \qquad \forall n,k \tag{5.14}$$

$$y_{nk} - z_{nk} = u_{nk} - u_{nk-1} \qquad \forall n,k \tag{5.15}$$

$$P_{H_{min},j} \leq P_{Hjk} \leq P_{H_{max},j} \qquad \forall j,k \tag{5.16}$$

$$H_{min,j} \leq H_{jk} \leq H_{max,j} \qquad \forall j,k \tag{5.17}$$

$$H_{jk} = \begin{cases} H_{jk-1} + H_{in,jk} + \eta_H P_{Hjk} & \text{if } P_{Hjk} \geq 0 \\ H_{jk-1} + H_{in,jk} + \frac{1}{\eta_H} P_{Hjk} & \text{if } P_{Hjk} < 0 \end{cases} \qquad \forall j,k \tag{5.18}$$

$$P_{EV_{min},i} \leq P_{EV,ik} \leq P_{EV_{max},i} \qquad \forall i,k \tag{5.19}$$

$$E_{EV_{min},i} \leq E_{EV,ik} \leq E_{EV_{max},i} \qquad \forall i,k \tag{5.20}$$

$$E_{EV,ik+1} = E_{EV,ik} + \eta_c P_{EV,ik} - d_{ik} \qquad \forall i,k \tag{5.21}$$

$$\sum_{n=1}^{N_G} P_{G,nk} - \sum_{j=1}^{N_H} P_{Hjk} = P_{D,k} + \sum_{i=1}^{N_{EV}} P_{EV,ik} \qquad \forall k \tag{5.22}$$

$$|F_{Lk}(P_{G,nk}, P_{H,jk}, P_{EV,ik}, P_{D,k})| \leq K_L \qquad \forall k \tag{5.23}$$

The EV equations thus enter the unit commitment problem as an extra set of constraints. They express that EV charging power needs to be within limits $P_{EV_{min}}$ and $P_{EV_{max}}$ and the battery state-of-charge (SoC) needs to be within limits $E_{EV_{min}}$ and $E_{EV_{max}}$. The charging power and SOC are related through Eq. 5.1 and this is where the driving data d_{ik} enter the problem.

Furthermore, in the multi-node model there is an additional set of constraints related to the line capacities. These extra constraints (Eq. 5.23) express in a general form that line flows F_L need to be within limits K_L. The exact form of this constraint depends on how the power flows are modeled. In the lossless two node example that we consider it is simply the surplus of generation minus demand at the one node that flows to the other node. In a DC load flow approximation one usually uses a linear relation of the form $F_L = HP$ where H (not to confuse with the hydro levels in Eqs. 5.17 and 5.18) represents a matrix with so-called distribution factors that relate nodal injections to line flows, calculated on the basis of electrical line properties. In a true AC load flow formulation Eq. 5.23 will be non-linear and the optimization problem becomes very difficult to solve. In an approximation method to take losses into account, one could add an extra term to the objective function that accounts for the losses.

By comparing constraints 5.16 to 5.18 with 5.19 to 5.21, one observes an interesting analogy. The equations for the pumped hydro plant are the same as for the EVs, except for the discharge due to driving term $-d_{ik}$ instead of the inflow term $H_{in,jk}$. In this analogy, the EVs can be considered as a series of leaky (negative inflow)

Table 5.1 – Overview of generation mix for the two different nodes. Installed capacity per fuel type in GW.

Type	North	South
Lignite	8	8
Coal	13	13
Gas	25	25
Wind Onshore	52	0
Wind Offshore	18	0
Solar	0	60
Hydro RoR	1	1
Hydro Pumped	20	20

hydro reservoirs that are (in our formulation) not capable of producing power, but whose reservoir levels need to be maintained within limits. How fast the reservoir is leaking thus depends on the driving patterns.

5.3 Simulation setup

5.3.1 Two node conceptual system

As a case study we perform simulations on a hypothetical two-node system that reflects the integration challenges of German RES. The installed capacities for the different generation technologies are based on German data, see Table 5.1. The idea behind this scenario is to take the 2025 scenario for Germany from the European Network of Transmission System Operators for Electricity (ENTSO-E), which gives the expected generation mix and the demand time series for that year. We then divide Germany in two nodes and assign all wind production to the northern node and all solar production to the south. Clearly, in reality wind and solar are more evenly distributed, but the point here is to get more or less realistic profiles of wind and solar production, fossil fuel generator capacities and retain the daily and seasonal time-correlation between wind and solar. Furthermore, we scale the EV demand data according to the German figures on passenger car usage. We emphasize that the aim of this case study is not to obtain quantitative conclusions for the German system, but to gain qualitative insights in the relations between transmission capacity and EV control.

5.3.2 Generator parameters

The capacities of the various generation technologies are listed in Table 5.1. Since data on the individual plants was not readily available, we divided the coal, lignite and gas plants in 1 GW units to run the unit commitment model. The plant characteristics are modeled based on some general assumptions, e.g. that gas plants have larger flexibility than coal and gas plants. The start-up costs for the fossil fuel generators have been determined by assuming a fixed start-up time per generation

Table 5.2 – Overview of generator parameters. Individual fossil fuel plant marginal costs vary within 10 % of the average values.

generator type	$P_{G_{min}}$ (MW)	$P_{G_{max}}$ (MW)	RU (MW/h)	RD (MW/h)	SUC (€)	SDC (€)	MC (€/MWh)
Coal	300	1000	300	300	54000 ± 3600	0	30 ± 2
Lignite	300	1000	300	300	45000 ± 3600	0	25 ± 2
Gas	200	1000	1000	1000	12000 ± 1000	0	60 ± 5
Wind	-	-	-	-	-	-	2
Solar	-	-	-	-	-	-	0
Hydro	-	-	-	-	-	-	3
VOLL	-	-	-	-	-	-	1000

type and setting the start-up costs equal to

$$SUC_n = \text{start-up time} \cdot MC_n \cdot P_{G_{min},n} \tag{5.24}$$

For coal and lignite, the fixed start-up times have been set to 6 hours, for gas to 1 hour. All generator data is shown in Table 5.2. We do not consider shut-down costs of plants, although the description in the unit commitment model allows us to do so. Renewable generators can ramp infinitely fast but their maximum output varies with time according to the wind and solar time-series that we use. It is important to emphasize that we do not model the renewable generators as negative load, so curtailment of them is possible. This can sometimes be attractive in order to avoid having to shut down and restart a fossil fuel plant. A virtual plant with a marginal cost equal to the value of loss of load (VOLL) has been included to ensure a feasible solution of the unit commitment. A small amount (2 GW) of run-of-river hydro (RoR) that was assumed to be non-dispatchable has been included as negative load. The overall efficiency (sequence of pumping and generating) of the pumped hydro is assumed to be 0.75, so $\eta_H = \sqrt{0.75}$.

5.3.3 Wind and solar time series

The meteorological solar data come from [87] and the wind data originate from [88]. The method to convert the meteorological time-series to power output has been described in [83]. Obviously the output of wind and solar depend on the weather conditions and large variations can be expected between the seasons. Fig. 5.1 shows the output (curtailment not accounted for) of wind and solar throughout the year. We run the model for all weeks of the year to get some insights in the seasonal differences. Furthermore, Fig. 5.1 shows that the maximum wind output is roughly 65GW (compared to the 70GW installed), whereas the maximum solar output amounts to little more than 45GW (60GW installed).

5.3.4 Other simulation details

Each simulation spans a whole year, and we run the model in periods of one week. The initial settings of the generator outputs for the next week are passed on from

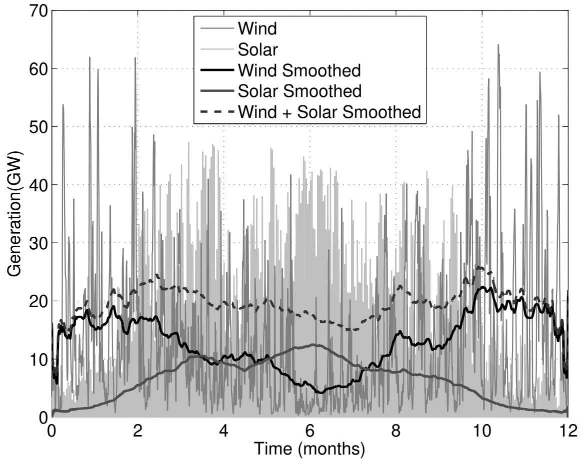


Figure 5.1 – Renewable energy generation time series

Table 5.3 – Overview of relevant simulation results for 6 scenarios.

Quantity	Scenario					
	0GW, Contr.	10GW, Contr,	0GW, Unc.	10GW, Unc.	0GW, No EVs	10GW, No EVs
Total Generation Costs (EUR)	1.46e10	1.36e10	1.52e10	1.42e10	1.36e10	1.26e10
Lignite Costs (EUR)	3.27e9	3.41e9	3.19e9	3.33e9	3.15e9	3.31e9
Coal Costs (EUR)	5.71e9	6.15e9	5.56e9	5.95e9	5.37e9	5.73e9
Gas Costs (EUR)	5.65e9	4.29e3	6.34e9	4.97e9	4.90e9	3.51e9
Hydro Generation (MWh)	4.92e6	4.54e6	7.14e6	7.42e6	6.99e6	7.39e6
Wind Curtailment (MWh)	4.60e6	1.17e6	6.22e6	2.02e6	1.07e8	2.55e6
Solar Curtailment (MWh)	1.99e5	2.74e3	1.33e6	2.17e5	1.53e6	2.53e5

the final setting of the previous week. For the EVs, an additional constraint that the SOC at the final time-step of the week has to be equal or higher than their initial SOC. This is to prevent that the batteries are always depleted by the end of the week. A similar constraint was formulated for the hydro reservoirs. The time-step of the simulation is 1 hour.

5.4 Results

5.4.1 Dispatch profiles

Table 5.3 shows simulation results for 6 scenarios, a combination of the three EV scenarios (controlled, uncontrolled and no EVs) and two scenarios for transmission capacity between the nodes (0 GW and 10 GW). Total generation costs here denote the yearly dispatch costs of all generators in the system, so there are no fixed costs included in this number. Dispatch profiles for a typical week in spring for the same

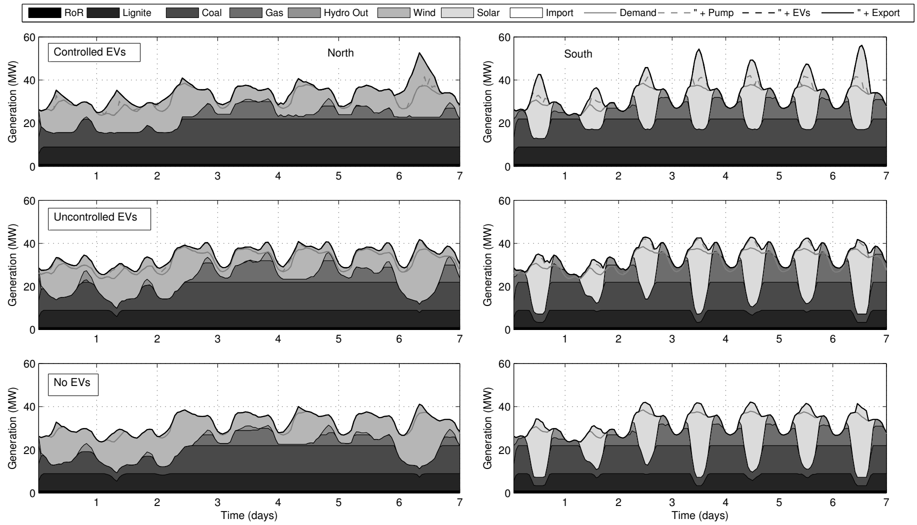


Figure 5.2 – Dispatch profiles for different vehicles scenarios without transmission between the nodes.

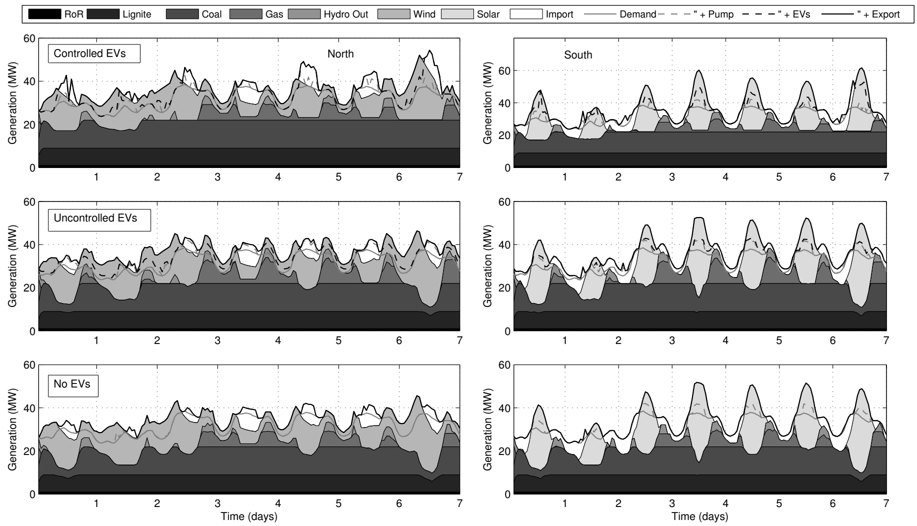


Figure 5.3 – Dispatch profiles for different vehicles scenarios with 10 GW transmission capacity between the nodes.

6 scenarios are shown in Fig. 5.2 and 5.3. We discuss the results in increasing order of complexity, so we start with the situation without EVs and without transmission - the bottom graphs of Fig. 5.2.

The most prominent feature of the dispatch profiles is probably the daily cycle of solar production and the much flatter wind profile. Of course, the latter is not always the case, but in this particular week in spring it is. We observe in the dispatch profile how during the periods with high renewables the thermal generators need to be shut down or ramped down. During the moments when demand is high and there is no solar or wind production, gas plants and pumped hydro plants also produce. One can also observe that hydro reservoirs are filled at the renewable production peaks.

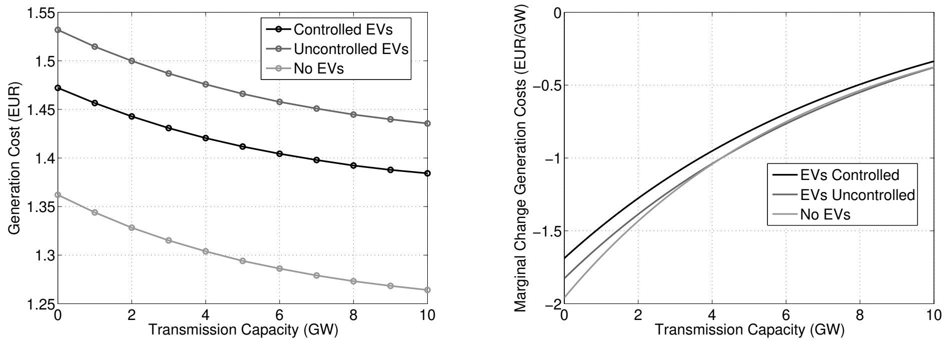
In the case without transmission and uncontrolled EVs, we notice a distinctly higher evening peak caused by EV charging. It can be seen that this extra demand is mainly met by dispatching extra gas plants - the darker profiles of coal and lignite are almost identical between the case without EVs and with uncontrolled EVs.

The most notable effect of the EV control (top graphs of Fig. 5.2) is to shift the EV load to the moments when renewable outputs are highest; during windy conditions in the northern node and during sunny conditions in the southern node. One also observes how EV control effectively shifts generation from the more expensive gas plants to the cheaper coal plants. Although this makes sense from a cost point of view (and total costs are what was minimized in the optimization), this leads to worse outcomes in terms of CO_2 emissions. In this chapter we do not further pursue the issue of CO_2 emissions, but appendix C explores the CO_2 emissions due to EV charging in more detail.

Furthermore, since EVs are mostly charged when renewable output is highest, one should note that in summer this can be *at the peak demand* of the system. A possible consequence of this fact, of which the further analysis is outside the scope of this chapter, is that when the renewable generation is not embedded at the distribution level, this might pose a challenge to the distribution grid.

Fig. 5.3 shows the dispatch profiles when a 10 GW transmission capacity between the nodes is in place. We see similar patterns as in the case without EVs, but the main difference is that the interconnection capacity equalizes the use of the fossil fuel plants in the nodes. As expected, the flows between the nodes are mainly present when renewable outputs are high. Interestingly, at first sight the flows do not seem to differ much between the EV scenarios. Summarizing, one could say that the inter-locational arbitrage equalizes the thermal generation profiles in the nodes (the envelope of all blue colors in Fig. 5.3) whereas the EV control (inter-temporal arbitrage) further shifts load from gas to coal (attempts to flatten the blue envelope).

Table 5.3 shows furthermore that essentially all cost differences between the scenarios are the results of shifting gas to coal generation plus the fact that for the same volume of gas generation, more efficient plants are being used. More detailed analysis showed that lower start-up costs contributed only marginally.



(a) Generation costs (b) Demand function for transmission

Figure 5.4 – Total generation costs as a function of transmission capacity and marginal change in generation costs (negative demand function) for transmission capacity for different EV scenarios

5.4.2 Demand function for transmission

Fig. 5.4(a) shows the total generation costs as a function of transmission capacity both for the controlled and the uncontrolled EV cases. As expected, the total generation costs decrease as a function of transmission capacity until some point where the effect saturates. Interestingly, however, the *difference* between the EV scenarios does not depend much on transmission capacity. In other words: whether or not EV management is present does not affect the value of transmission capacity. Fig. 5.4(a) also shows that, dependent on how much transmission capacity is in place, EV control leads to the same amount of savings on generation costs as a substantial amount of transmission capacity.

Based on Fig. 5.4(a) we can also deduce some insights in the socially optimal amount of transmission capacity. In theory, at the optimum, the marginal value of the transmission capacity should equal its costs. The derivative of the curves in Fig. 5.4(a) can be interpreted as the (negative) demand function for transmission capacity and they are plotted in Fig. 5.4(b). If one unit of transmission capacity would cost, say $1.4 \cdot 10^8$ EUR/GW, then the intersection of a horizontal line at $-1.4 \cdot 10^8$ EUR/GW with the demand functions would denote the optimal transmission capacity between the nodes. We observe that it differs approximately 1GW between the uncontrolled and controlled EV cases. So EV control always lowers generation costs, more or less independent of transmission capacity. Because of this independence, the optimal amount of transmission capacity only modestly depends on whether or not EV control is in place.

5.4.3 Further analysis

In the preceding analysis we considered results regarding the interrelations between transmission capacity and EV control. Now we further explore conditions to which those interrelations of transmission and EV control are particularly sensitive.

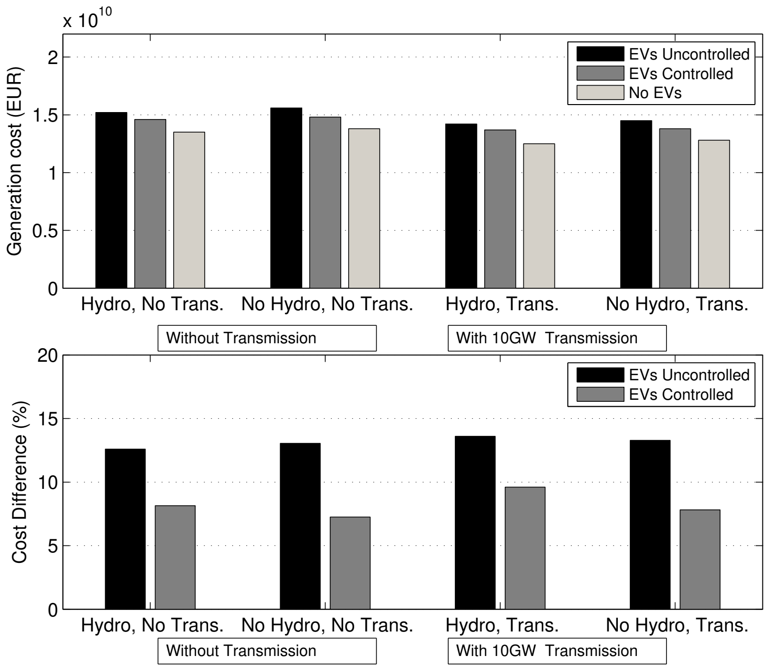


Figure 5.5 – Percentual difference in total generation cost for EV scenarios in comparison with no EVs, for different pumped hydro and transmission capacities.

Sensitivity to pumped hydro storage Fig. 5.5 shows how total generation costs depend on transmission and whether or not pumped hydro storage is in place. In the bottom graph, only the percentual cost difference with the no EV scenario are shown. We interpret these graphs by first recalling that there are basically three mechanisms available to deal with the variable renewables: transmission (inter-locational arbitrage), EV management and pumped hydro storage (both inter-temporal arbitrage). It can be seen that the value of EV control (the difference between the grey and black bars in the bottom graph) is only markedly lower in the case that there is both transmission and hydro-capacity in place, although even in this case the cost difference is substantial. From this we conclude that especially if one of the two alternative arbitrage mechanisms of transmission and pumped hydro is lacking, the value of EV management becomes more prominent.

Sensitivity to RES penetration levels Fig. 5.6 shows the total generation costs for increasing RES penetration. The extra 50% and 100% RES are with respect to the values quoted in Table 5.1. Shown in the lower part of the same figure are the percentual differences between the EV cases and the case without EVs. They can be interpreted as the additional generation costs to accommodate the extra EV demand.

The figures show that total generation costs decrease only modestly for the higher RES levels. The percentual extra costs of accommodating the EVs actually increase

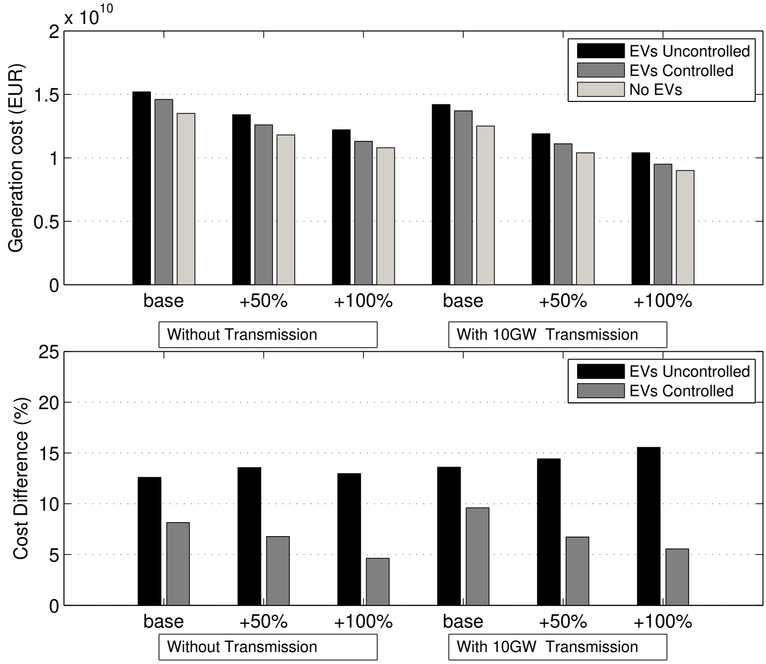


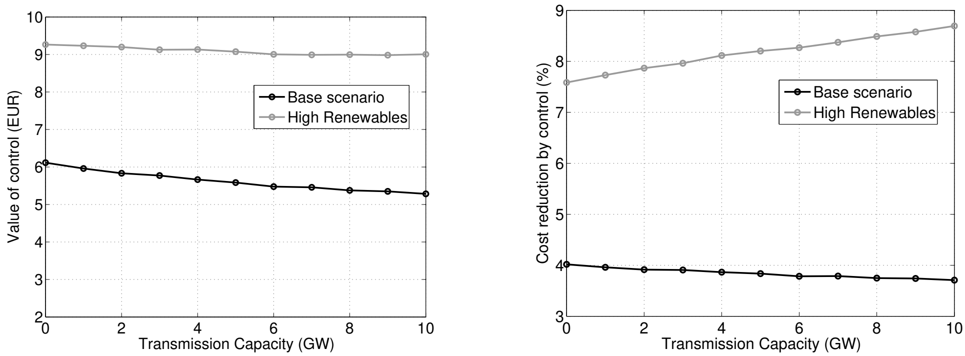
Figure 5.6 – Total generation costs and percentual difference of the cases with EVs for the base case and case where RES has been increased by 50% and 100%.

slightly in the uncontrolled scenarios, but they decrease quite significantly for the controlled case. This can, however, not be regarded as surprising, since the increased RES penetration makes the demand for arbitrage larger.

The most important point that Fig. 5.6 reveals is, however, the following. We observe that in the high RES the value of control (the difference between the two bars in the bottom graph) actually *increases* with higher transmission capacity. This is a counter-intuitive result, since the common understanding, and the picture that emerged from this analysis so far, is that transmission and control are substitute technologies. One can explain this result as follows: at some point RES production is so high that we need the inter-temporal arbitrage potential in both nodes to absorb the excess wind or solar in one node. In this case, one needs the transmission capacity to use the EV control in the other node. At these very high levels of RES penetration, the two technologies thus in fact need each other and are complementary.

The value of EV control under different conditions The value of EV control and its relation to transmission capacity can be analyses by considering the difference in total generation costs between the uncontrolled and the controlled EV scenarios. Figs. 5.7(a) and 5.7(b) shows these in both absolute and relative terms as a function of transmission capacity for two cases: the base case and the high (200%) RES case.

One observes how, in absolute terms, the value of control decreases with transmission capacity, although the decrease in the high RES case is very small. This



(a) Absolute value of control

(b) Relative value of control

Figure 5.7 – Absolute value of control (difference in total generation costs) and relative value of control (percentual reduction in total generation costs) as a function of transmission capacity

decreasing trend can partially be explained by the fact that the absolute value of generation costs itself decreases with increasing transmission capacity. By contrast, Fig. 5.7(b) shows how much EV control reduces generation costs relatively compared to the uncontrolled EV scenario. Here we can confirm the notion that we found in the RES sensitivity analysis: for large RES penetration levels, the value of EV control becomes higher with increased transmission capacity. Under such conditions, EV control and cross-border transmission thus become complementary technologies.

Seasonal dependencies Fig. 5.8 shows how generation costs and the differences between various EV and transmission scenarios depend on the time of year. These figures provide additional insights on the value of EV control and transmission and their seasonal dependencies. When interpreting these results, it is instructive to recall Fig. 5.1 that shows the wind and solar output throughout the year. In the top graph of Fig. 5.8 the total weekly generation costs are plotted for the different EV and transmission scenarios. It can be seen that generation costs are highest in winter, when demand is highest and the combined generation of wind and solar is not so high. Loosely speaking, the generation costs reflect how much fossil fuel generation is needed to meet the demand, so it is not surprising that this is determined by the residual load (demand minus renewable generation).

The difference in generation costs between the scenarios with and without EVs (displayed in the second graph of Fig. 5.8) show only some small seasonal dependence for the controlled cases, and the effect of transmission on this dependence is negligible. For the controlled cases, the extra generation costs are lowest in spring and summer, due to the fact that EV control is especially effective to handle the more periodic solar generation patterns.

The value of 10GW transmission capacity can be determined by considering the difference in generation costs with and without the 10GW transmission capacity.

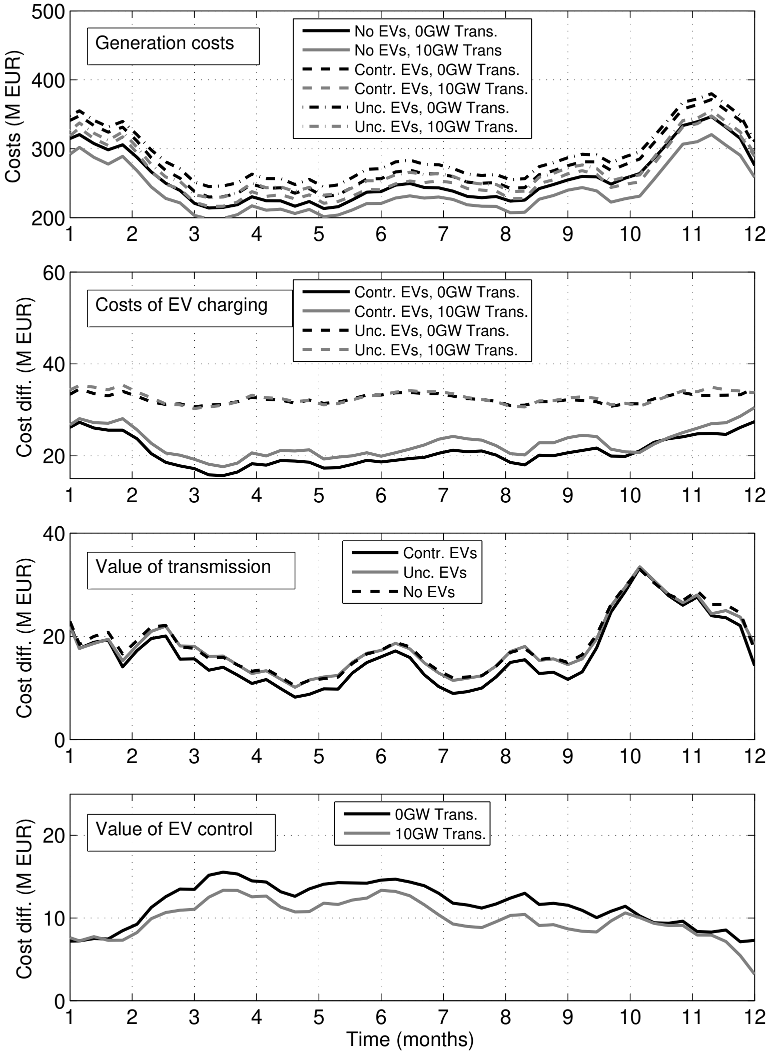
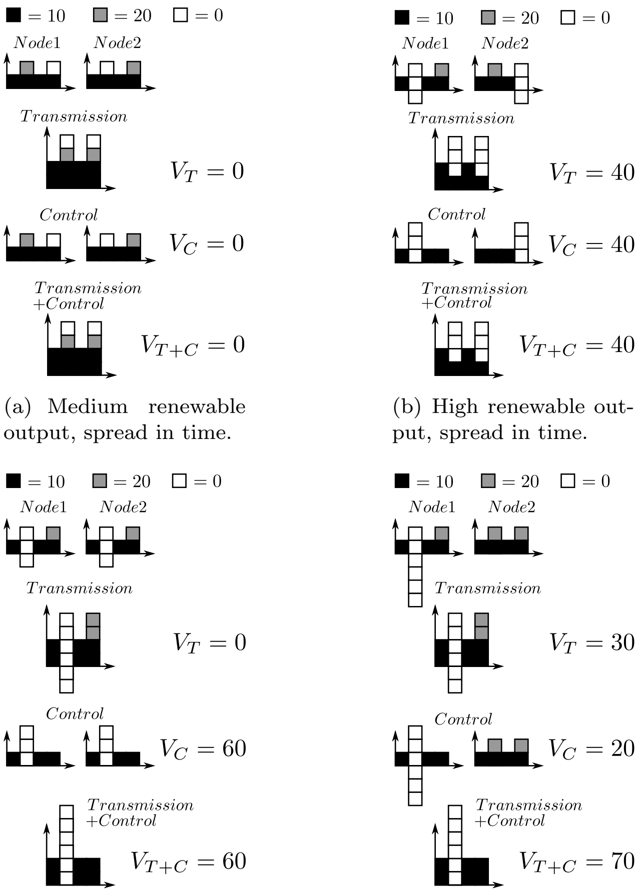


Figure 5.8 – Weekly generation costs, costs of EV charging, value of transmission and value of EV control for all weeks of the year. All graphs are smoothed by using a moving average filter with a window of 5 weeks.

The third graph in Fig. 5.8 shows this quantity for the whole year. For most of the year, the value of transmission is lower when there are controlled EVs - this is in line with the conclusions from Fig. 5.4. Also, there is a distinct peak in the value of transmission around month 10. This is exactly when the combined wind and solar generation was at its highest (see Fig. 5.1). Interestingly, at this peak the value of transmission capacity did *not* depend on EV control anymore. Actually, the unsmoothened graphs (not shown here) revealed that the value of transmission was even slightly higher in the controlled EV case. More detailed analysis of these situations showed that in this case wind generation in the northern node was considerably higher than demand in that node and EVs in the other node were able to increase their demand, thereby replacing fossil fuel. So in excess wind and/or solar generation the combination of transmission and EV control is beneficial and the ability to control EVs in fact adds to the value of transmission. This shows once more the complementary nature of the two technologies for those situations. In the base case RES scenario these periods are quite rare, but from the RES sensitivity analysis we draw a similar conclusion.

The value of EV control, given by the difference in EV charging costs between the controlled and uncontrolled scenario, is depicted in the bottom graph of Fig. 5.8. This number is highest in spring and summer, when there is a reasonably balanced mixed of wind and solar generation. In these situations the EVs are optimally benefiting from renewable production. The reason that the value of EV control fluctuates has to do with the price differences between gas, coal and lignite. Sometimes, dependent on the combination of inelastic electricity demand and renewable generation, EV control leads to a shift from gas to coal, which results in a large price difference. On other moments, the shift is from coal to lignite, which has a much smaller difference and hence the shifting of load has a lower value associated with it.

A conceptual interpretation of the results We consider it instructive to illustrate the results on the complementarity of EV control and transmission capacity using a schematic diagram of a hypothetical two node system. Fig. 5.9 shows the dispatch profiles for this system. There are four time-steps in which the demand varies between one and two. There are two dispatchable generation technologies (say, coal and gas) and one renewable technology (say wind) with zero marginal cost. Furthermore, there is an opportunity for demand response to move one block of demand per node. For four different wind situations, the diagrams indicate the value of transmission (when the two nodes become one), the value of control (when one block of demand is shifted) and the value of both transmission and control. In case 5.9(a), when there is only little wind, there is no value in any of the technologies. In case 5.9(b) there is more wind and in the base scenario wind needs to be curtailed (indicated by the white blocks below the x-axis). In this case both transmission and control have a value: they effectively displace the use of gas by coal and prevent curtailment. There is, however, no extra value in the combination of the two. In case 5.9(c), the wind in the two nodes produces at the same moments and one observes that there is no value in transmission, only in control. Again, the combination of transmission and control adds no extra value. In the final case 5.9(d) where there is



(a) Medium renewable output, spread in time.

(b) High renewable output, spread in time.

(c) High renewable output, coinciding.

(d) Very high renewable output, only in node 1.

Figure 5.9 – Schematic representation of dispatch results in a hypothetical two node system for 4 time-steps. V_T, V_C and V_{T+C} denote the value of transmission, value of control and value of transmission and control, respectively. Control means that one unit of demand can be shifted in time. Per unit costs of the black, grey and white technologies are 10, 20 and 0 respectively. Curtailment occurs if a white block is below the x-axis.

only a very high wind production in the one node, we observe that the combination of transmission and control has a higher value than the sum of the individual values. In this case, one can consider the two technologies complementary.

Based on these diagrams one can understand the observed results in Figs. 5.6, 5.7 and 5.8 better. It explains why only in the high RES case or in those weeks of the year with very high RES output there exists a complementarity effect between control and transmission. It also explains, to some extent, the importance of the exact timing of the RES output in both nodes. If wind and solar production happen to coincide, there is less value in transmission. Indeed, in Fig. 5.8 we observe that the value of transmission is lowest in spring, when wind and solar are more or less in balance.

5.5 Conclusions

In this chapter we aimed to gain insight in the interrelations between demand response in the form of EV control and transmission capacity between neighboring nodes. We formulated a least cost unit commitment model that includes EV charging as optimization variables and studied a conceptual two node power system with a high penetration of renewable energy sources. Below we summarize the most important findings of this work:

- In our case study, controlled EV charging always reduces generation costs and hardly depends on how much transmission capacity is in place.
- In the base case scenario, cost savings due to EV control come almost entirely from a shift from gas to coal. For the remaining gas generation, the more efficient plants are being used. Fewer start-ups contribute only marginally to the cost reduction. When RES penetration is very high, the avoidance of curtailment leads to extra cost reductions.
- Effectively, in our modeled system there are three options for arbitrage: pumped hydro, EVs and cross-border transmission. The value of EV control becomes more pronounced if one of the other two are not present.
- When the penetration of renewables is higher than the base case scenario, transmission capacity and EV management become complementary in the sense that their combined effect is larger than the sum of their individual effects. Transmission is needed to transport power to where the EVs can absorb it.
- The value of transmission and control can be largely understood in terms of the demand for arbitrage. We showed, however, that one cannot solely explain this demand for arbitrage in terms of the RES penetration level. Details like the timing of renewable generation in neighboring nodes and the relative magnitudes of different renewable technologies do play an important role.
- One could argue that the extreme cases that we considered are unrealistic, but in the light of European RES targets for the year 2050 this is not the case.

Moreover, this study stresses the importance of research of fully renewable power systems, since much conventional knowledge and intuition on traditional power systems no longer hold.

A number of remarks should be made in reflection of our results and findings. Clearly the conceptual two node system, though inspired by German figures, is a model of reality and it is hard to draw quantitative conclusions from it. Therefore, the second case study presented in [76] focuses on a more realistic setting by considering real European generation and transmission scenarios for the year 2025. Furthermore, an important assumption that we have made is the assumption of perfect forecasts of renewable energy production. Loosening this deterministic assumption is a crucial aspect for future research in this area since it will target the second (next to variability) difficult characteristic of RES: uncertainty. Related to this is the assumption of perfectly known driving patterns and the willingness of EV drivers to control their EV charging. More detailed analyses that investigate this aspect are therefore also recommended. In such analyses that take uncertainty into account, more advanced optimization and control algorithms need to be applied. Finally, we consider it worthwhile to include investment costs of new generation in the analysis. In this study we focused only on variable production costs of a given portfolio, but from a systems point of view one wants to minimize total generation costs including fixed costs. Moreover, in such an analysis it will be more natural to include the vehicle-to-grid concept, since it can reduce the need for back-up generation capacity. Within the scope of the present study, however, the results strengthen the confidence that an interconnected *and* intelligent electricity infrastructure is a promising way to realize a fully sustainable energy system.

Chapter 6

Renewable energy sources and responsive demand. Do we need congestion management in the distribution grid?

This chapter is based on [89].

6.1 Introduction

Two major technological trends that may play an important role in a transition towards a low-carbon energy system are the introduction of renewable energy sources (RES) and the advent of electric vehicles (EVs). As the penetration of RES progresses, electricity will increasingly be supplied by fluctuating, weather-driven sources like solar and wind energy. This has consequences for the functioning of the electricity system. One paradigm for dealing with variable RES is the concept of a smart grid, which may facilitate demand responsiveness. Currently, the price-elasticity of electricity demand is low and the ability to shift load is, especially for small consumers, limited. EVs, on the contrary, could form a flexible load of significant magnitude. They are therefore capable of reacting to and influencing wholesale electricity prices. By doing so they have the potential to support renewable energy sources [46].

However, when fleets of EVs are reacting to wholesale prices, they will do so in a correlated way, since they react to the same electricity price. When EVs postpone charging until the electricity price is at its lowest, they will create a peak demand at that moment. Of course there is a feedback mechanism: when the EVs are expected to add to demand significantly at that moment, the resulting price increase will be taken into consideration ex ante and EV demand will spread to some extent, see e.g. [39]. However, as was for example shown in [38], when the share of variable renewables increases, electricity demand and the wholesale price become increasingly decorrelated because the wholesale price depends on the instantaneous load *and* production of electricity. In other words, when wind and/or solar generation are high, there could be relatively low wholesale prices even if electricity demand is high.

Owing to the potentially large impacts of a high share of EVs in power systems, a large body of literature on this topic has been developed in recent years. A broad overview of EV studies was given in [50]. The problem of an aggregator who minimizes the charging costs of EVs by reacting on time varying prices (potentially driven largely by renewable energy production) was studied in e.g. [39], and in combination with providing frequency regulation in e.g. [78]. EVs also received much attention because of the potential role in supporting renewable energy sources, e.g. in [42] and [46]. Furthermore, there has been a strong focus on the grid impacts of EVs and how charging can be controlled in order to alleviate potentially severe impacts, such as [55], [44], [69] and [59], which gives an overview of such studies.

A common finding of many of these studies is that controlled charging of EVs can have significant value for various actors in the power system. Only a few studies, however, have analyzed the problem of satisfying different objectives such as minimizing the cost of vehicle charging, frequency regulation and providing balancing services, in combination with grid constraints.

In [90], the problem of EV charging under grid constraints was investigated. The essence of the method that was applied in this paper was first to minimize the cost of charging, then to evaluate if all grid constraints are satisfied, and if not, then to communicate available grid capacity to the EV aggregator who, finally, performs the charging cost optimization again, now including the EV power constraints that follow from the grid conditions. It was shown that this method is successful in not exceeding grid limitations and can even be applied to quite complex grid topologies.

[91] investigates how dynamic day-ahead grid tariffs can be used to alleviate distribution grid congestion caused by electric vehicle charging. In this case, the exact congestion tariff is set by the distribution system operator (DSO) using forecasts of wholesale prices and EV trips. In this formulation of the problem, the DSO first mimics the EV aggregator and computes the minimum-cost EV charging profile. Next, he computes the congestion tariff based on the locational marginal price formulation using the shadow price of grid congestion in the grid. However, this approach does not take into account the inter-temporal constraints of EV charging. A somewhat heuristic method for determining the appropriate 'congestion' level was applied to circumvent the problem that arises when inter-temporal constraints are ignored: if one only charges a congestion fee on the expected time of congestion, then the EVs will ajust their behavior and congestion will likely occur just before and after the time with congestion fee.

[92] provides a comprehensive overview of different methods for relieving distribution grid congestion caused by EV charging. Three methods are discussed: 1) a distribution grid capacity market, 2) advance capacity allocation and 3) a dynamic grid tariff. Of the two formerly discussed papers, [90] falls in category 1 and [91]

in category 3. [92] concludes that there is always a trade-off between complexities, values and risks for the stakeholders. No single strategy has a clear advantage over the others.

The goal of this chapter is to investigate possible mechanisms for aligning EV responsive demand with constraints resulting from limited distribution grid capacity more thoroughly. To this end, we first present a mathematical description of optimal EV charging in the current situation and analyze the problem that arises when the share of variable renewable energy increases. We then describe and formalize a number of congestion management mechanisms that could alleviate the problem. We analyze the different mechanisms in a case study in which we make use of empirical data on renewable energy production and driving behavior. We will also comment briefly on the challenges caused by uncertainty and on the IT requirements of the different congestion management mechanisms.

This chapter adds a number of novel aspects to the scientific literature. The first is that, as the chapter title suggests, we focus explicitly on power systems with a high share renewable energy sources, because especially in these systems price-responsive demand is expected to play an important role. A central theme of this chapter is that the influence of variable RES on the electricity price makes the need for congestion management in the distribution grid more urgent. Secondly, we present a mathematical formalization of different distribution grid congestion management methods in relation with EV charging, which may become the single largest source of flexible electricity demand at household level. In addition, we perform a numerical case study in order to compare the performance of the different congestion management mechanisms, producing new insights into the advantages and limitations of the various methods. Because the case study is based on empirical data of driving patterns, electricity prices, renewable energy production and network load, we are able to evaluate the congestion management methods in realistic situations.

6.2 Problem analysis

6.2.1 The need for congestion management due to the weakening corellation between wholesale electricity prices and demand

In an electricity system without much variable renewable energy, electricity prices rise when demand is high. This provides an incentive for EVs to be charged during off-peak hours, so the charging of EVs should not add significantly to the peak flows through the electricity network. However, in the presence of a significant volume of wind energy, which will likely be the case by the time that these large numbers of EVs have been introduced, this dynamic can be expected to change.

A consequence of a large volume of wind energy will be that the current correlation between the wholesale electricity price and network flow will become weaker. This means that if the charging of electric vehicles is driven by wholesale electricity prices, this may lead to network flows in excess of the capacity of distribution grids. A typical case is when wind output is maximal during peak consumption hours. This may result in low wholesale prices despite the fact that consumption is high, and responsive demand reacting to the price could therefore cause even higher network loads. For a typical time period, Fig. 6.1 shows how system load, wind generation, the electricity price and network load are correlated. The data are taken from the Dutch electricity system [93], but we expanded the current electricity generation portfolio with two different installed wind capacities. For the network load we use the standard household load profile that is used for net planning purposes in the Netherlands [22]. During the observed period, there is a distinct peak in wind power production that lasts roughly one day. It is important to observe how wind generation reduces the electricity price significantly in the case with 15 GW of wind generating capacity and, as a result, the electricity price profile shows quite a different shape than the network load profile: at some moments with high network load the electricity price is low. In the case with only 2 GW of wind, the electricity price follows the demand curve more closely. One could argue that this phenomenon of decoupling, due to the specific timing of the wind power production and demand, is a relatively rare event, but since the networks need to accomodate the maximum demand, even a limited hours per year can be problematic.

In the case that price-responsive EV demand will react on a low wholesale price while network load is high, a congestion management mechanism will be necessary in order to prevent network congestion. This mechanism will need to influence EV charging behavior in such a way that network constraints are not violated. An additional objective is that it should minimize the additional cost to EV owners as compared to charging when wholesale prices are lowest. A final consideration is the feasibility in terms of information, computation and communication requirements.

6.2.2 Minimum cost EV charging formulation

We will first summarize our EV charging model. A more elaborate description of the optimization formulation of an aggregator that minimizes charge costs of a fleet of EVs is provided in [38] and chapter 2 of this thesis.

We assume that real-time pricing of electricity will have been implemented and that EV owners, represented by an aggregator who manages a fleet of EVs, therefore have their vehicles programmed to minimize the electricity cost of charging. The aggregate demand of the EVs is assumed to be large enough to influence the wholesale electricity price, see also [39]. We differentiate between electricity consumed by EVs and electricity consumed for other purposes. We will refer to the latter as 'baseline electricity consumption', which we assume to be perfectly price-inelastic.

Demand of electricity $P_{D,k}$ is given by:

$$P_{D,k} = P_{D0,k} + P_{EV,k} \tag{6.1}$$

where $P_{D0,k}$ is the baseline demand and $P_{EV,k}$ is the extra demand of the EVs at time-step k.

We include an EV-load dependent part in the electricity price:

$$\lambda_k = \alpha_k + \beta P_{EV,k} \tag{6.2}$$

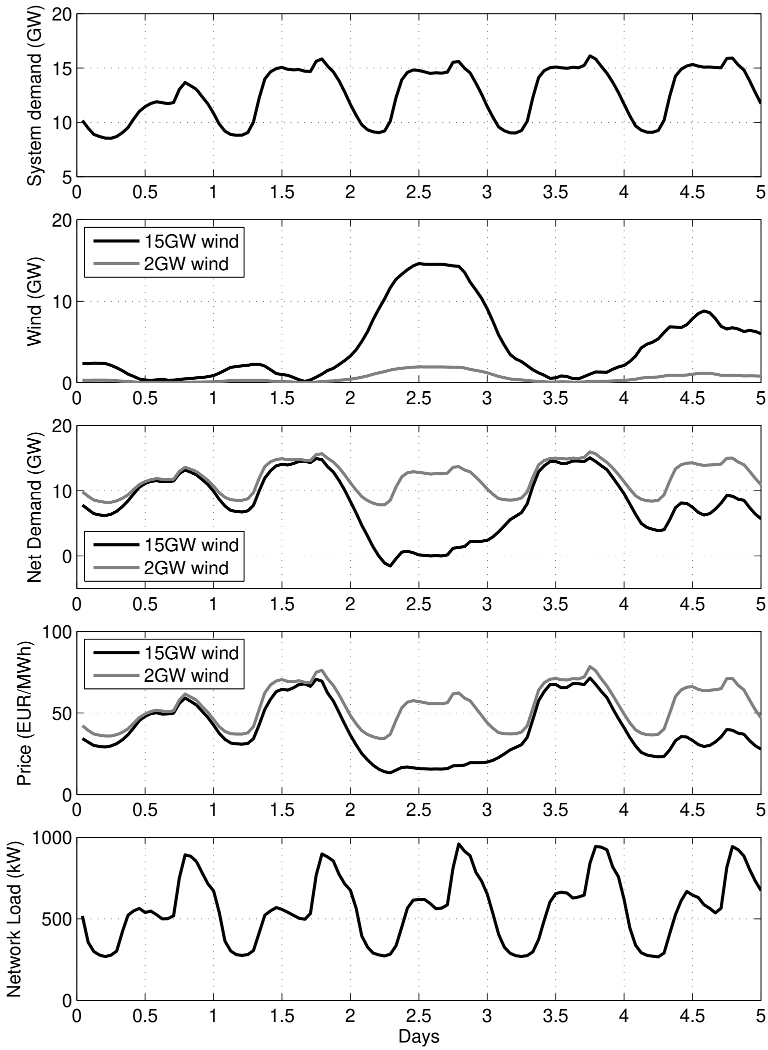


Figure 6.1 – From top to bottom: total system demand, wind generation, net demand, electricity price and distribution network load. All graphs are for the same 5 day period. The second, third and fourth figures show the differences between the installed wind power capacity of 2GW and 15GW.

where α_k is the baseline electricity price at time k and $\beta P_{EV,k}$ the EV dependent part. As outlined in chapter 2, the idea is to linearize the electricity price around a certain average price and use the merit order of power plants to estimate the sensitivity parameter β. This approximation allows for a quadratic programming formulation of the EV charging problem, while it still includes the feedback of EV charging on the electricity prices. If this feedback would not be taken into account, all EV demand would be programmed in a short time interval with the lowest prices in the optimization period, causing unrealistically high peaks in demand.

Next to the electricity price λ_k we will also consider the time-dependent network tariff μ_k. The minimum cost charging problem then takes the following form:

$$\min_{P_{EV,ik}} \sum_{k=1}^{N_k} (\mu_k + \alpha_k) P_{EV,k} + \beta P_{EV,k}^2 \tag{6.3}$$

$$\text{s.t.} \quad P_{EV,k} = \sum_{i=1}^{N_{EV}} P_{EV,ik} \qquad \forall k \tag{6.4}$$

$$P_{EV_{min},i} \leq P_{EV,ik} \leq P_{EV_{max},i} \qquad \forall i, k \tag{6.5}$$

$$E_{EV_{min},i} \leq E_{EV,ik} \leq E_{EV_{max},i} \qquad \forall i, k \tag{6.6}$$

$$E_{EV,ik+1} = E_{EV,ik} + \eta_c P_{EV,ik} - d_{ik} \qquad \forall i, k \tag{6.7}$$

where optimization variable $P_{EV,ik}$ denotes the charging rate of vehicle i out of a total of N_{EV} at time k and state variable $E_{EV,ik}$ denotes the battery state-of-charge (actually state-of-energy). Technical vehicle parameters are the following: η_c denotes the charging efficiency per vehicle, $E_{EV_{min},i}$ and $E_{EV_{max},i}$ the minimum and maximum state-of-charge and the charging power limits are given by $P_{EV_{min},i}$ and $P_{EV_{min},i}$. The state equation Eq. 6.7 relates battery state to charging rate and it implicitly contains the assumption that vehicles cannot deliver energy back to the grid: $P_{EV_{min},i} = 0$. The term $d_{i,k}$ represents the discharges due to driving and thus depends on the driving patterns of the EV owners. In a way, this term can be considered to reflect individual consumer preferences, since it determines the level of flexibility of each EV. Drivers covering large daily distances can not afford to wait several days to recharge.

6.2.3 Simulation of the current situation (flat grid tariff)

To demonstrate why there could be a need for congestion management in distribution grids, we run a simulation where a fleet of EVs charges according to the formulation above. Part of this fleet is connected to a certain distribution grid with a certain capacity and a perfectly inelastic electricity load that representes roughly 1000 households. We assume that 50% of the households owns an EV and we represent the resulting fleet of approximately 500 EVs by 25 typical driver profiles, see also [39] and appendix D of this thesis. Furthermore, we assume that the cable has a peak load (occurring during only one hour of the simulated year) that is exactly equal to the cable's safe capacity. The simulation spans a period of a year in a so-called rolling horizon optimization scheme. This means we solve the optimization problem described by Eqs. 6.3-6.7 for a period of 5 days (using a 1 hour time-step,

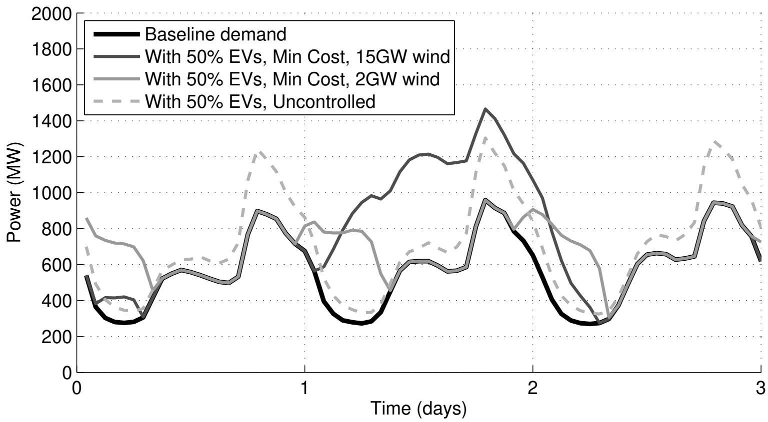


Figure 6.2 – Comparison between load profiles resulting from minimum cost EV charging for two wind capacities and uncontrolled EV charging.

so 120 time-steps), then implement the control actions for the first day, then move the horizon by one day, etc. The rolling horizon optimization has two important advantages: there are no end-point effect towards the end of each optimization period and secondly, this formulation allows for an easier adaptation to include uncertain forecasts that are updated each day. We emhasize that this uncertainty is not taken into account in this chapter, which implicitly means we assume perfect RES and load forecasts.

We run a simulation of a year. The EVs are charged as described above and the network tariff μ_k is assumed not to depend on time. For comparison, we also simulate an uncontrolled charging profile that occurs if EVs simply start charging upon arrival at home. (See [28] for more information on the construction of the uncontrolled charging profile.) Fig. 6.2 shows the network load that results from the minimum cost charging formulation described above for the same period that was shown in Fig. 6.1. One observes a strong peak in network demand in the evening of day 2. This is the result of the fact that the EVs postpone their charging until the period with the lowest price. In the case with only 2GW of wind installed, this peak is absent. One also observes how the minimum-cost charging strategy can even lead to a higher network peak than the uncontrolled charging scenario.

6.3 Congestion management mechanism design

We will analyse the effectiveness and implementation issues of the main three congestion management mechanisms that are discussed in the literature: a dynamic grid tariff, advance capacity allocation and a distribution grid capacity market. In this section we will discuss how we modeled these mechanisms.

A congestion management mechansim would limit the combined load of the EVs plus the inelastic baseline load to the capacity K_l of a certain distribution asset, say a cable l. The mathematical formulation of this constraint reads:

$$\sum_{i \in EV_l} P_{EV,ik} + P_{l,k} \leq K_l \qquad \forall k, l \tag{6.8}$$

where EV_l denotes the subset of EVs connected to a particular cable l and $P_{l,k}$ the inelastic baseline load. The minimization of equation 6.3 in combination with constraints 6.4 to 6.7 and this extra constraint leads to the theoretical minimum energy costs of a group of EVs on a certain cable while respecting the cable limits. An optimal congestion management mechanism, either price-based or capacity-based, is thus expected to yield the same EV charging profile and costs.

6.3.1 Dynamic network tariff

The first mechanism that we discuss is a dynamic network tariff that introduces a time-varying network price per kWh for using the network. The theoretically optimal network tariff would be the lowest tariff that would cause the EV load plus baseline demand to be just lower than network capacity. This can be formulated as a bi-level programming problem of the following form.

$$\min_{\mu_k} \sum_{k=1}^{N_k} \mu_k \tag{6.9}$$

$$\text{s.t.} \quad \sum_{i \in EV_l} P_{EV,ik} + P_{l,k} \leq K_l \tag{6.10}$$

$$\min_{P_{EV,k}} \sum_{k=1}^{N_k} (\mu_k + \alpha_k) P_{EV,k} + \beta P_{EV,k}^2 \tag{6.11}$$

$$\text{s.t.} \quad E_{EV_{min},i} \leq E_{EV,ik} \leq E_{EV_{max},i} \tag{6.12}$$

$$P_{EV_{min},i} \leq P_{EV,ik} \leq P_{EV_{max},i} \tag{6.13}$$

$$E_{EV,ik+1} = E_{EV,ik} + \eta_c P_{EV,ik} - d_{ik} \tag{6.14}$$

$$P_{EV,k} = \sum_{i=1}^{N_{EV}} P_{EV,ik} \tag{6.15}$$

This problem formulation states that the task of the DSO (the leader) is to find the lowest time-varying tariff such that when the EV aggregator (the follower) minimizes his charging costs, the sum of inelastic demand and EV demand does not exceed line capacity K_l. Note that this formulation assumes a welfare-maximizing DSO, which is an approximation of a perfectly regulated or an ideal publicly owned DSO. Relaxation of this assumption is outside the scope of this chapter, as network regulation is a different and well-developed line of research.

In e.g. [94] it is shown that even the linear version of a bi-level programming problem is NP-hard and generally requires sophisticated algorithms to solve. In this case, however, because the follower problem is quadratic in nature, the complexity increases further, even in the case of perfect information on the leader's side.

The presence of inevitable uncertainties makes this a stochastic problem that could render some solution approaches infeasible. We therefore consider two alternative approaches that have certain practical advantages: one capacity-based approach and one distributed and iterative price-based approach.

6.3.2 Advance capacity allocation

The idea behind the advance capacity allocation method is that the DSO announces ahead of time what the free capacity of the network is, i.e. the capacity that is not needed to serve inelastic demand. A practical implementation of this formulation would involve the network operator communicating the forecasted time-dependent available capacity $K_l - P_{l,k}$ to the EV aggregator ex-ante. Another possibility would be for the network operator to take on the role of the EV aggregator himself, but this would constitute a departure from the principle of unbundling network-related and commercial activities. In case of a single aggregator, the aggregator can simply include the announced free capacity in the optimization formulation. Essentially he thus includes constraint 6.8 in the optimization problem described by 6.3 to 6.7.

In a case with multiple EV aggregators, matters become more complicated. A natural approach would be for the DSO to collect the demand bids (for each time-step) for network capacity by the aggregators and to auction the free network capacity. Once the market is cleared, the DSO communicates the allocated capacity per time step to each aggregator. An issue that complicates the allocation by auction is that the demand bid for capacity in a certain time-step depends on what whas allocated in previous and future time-steps. It would thus require iterations to circumvent this problem, which seriously increases the complexity of this mechanism. In the next subsection we discuss a mechanism that is more suitable for the case of multiple aggregators.

Other allocation methods could also be possible, for instance on the basis of the maximum willingness to pay for network capacity. If the aggregators would submit their demand for network capacity ex ante (computed periodically, e.g. once per year) to the DSO, in case of congestion he would allocate the available network capacity based on these bids. The aggregators could be asked to submit bid functions, but perhaps a single maximum willingness to pay could also work. They would not need to update their demand frequently, as in principle their maximum willingness to pay should remain constant over time. This method has simplicity and transparency as advantages, but does not guarantee that all EVs always have enough energy in their batteries that all intended vehicle trips can be made. As we take the driving behavior as a constraint in our analysis, we will not pursue this option further.

6.3.3 Distribution grid capacity market

The problem of finding the optimal dynamic grid tariff described by Eqs. 6.9 to 6.15 can also be approached iteratively and in a distributed way. This method is more suitable in case of multiple aggregators. Essentially, this approach consists of the following steps: first the aggregators perform the optimization without a network tariff and communicate their charging schedule to the DSO. The DSO then evaluates whether the network constraints are satisfied; if not, he raises the network tariff during the moments when network capacity is exceeded. The aggregators recalculate their charging schedules based on the new grid tariff, communicate their demand to the DSO, etc. This procedure is repeated until it converges, which results in a certain grid tariff and a binding charging schedule. This scheme was labeled a distribution grid capacity market [92] and was also investigated by [95], who shows that this works in a situation with multiple aggregators by demonstrating that a distribution grid capacity market can be solved in a distributed way and yields the optimal load profiles without the need for information sharing between the aggregators. We use the same algorithm as [95], which is briefly described below. For notational convenience, instead of using subscript k, we now use bold fonts to denote vectors with a length of the number of timesteps in the optimization. Furthermore, we drop superscript N to denote the network tariff, so $C_t^N \equiv \mathbf{C}$. The index j denotes the iteration number. The algorithm consists of the following steps:

$\boldsymbol{\mu}^0 = 0$
Solve Eq. 6.3 s.t. Eqs. 6.4 to 6.7 to obtain $\mathbf{F}^j = \mathbf{P}^*_{\mathbf{EV}} + \mathbf{P_l}$
$\boldsymbol{\mu}^{j+1} = \boldsymbol{\mu}^j + \gamma \max(\mathbf{0}, \mathbf{F}^j - K_l)$
Stop if $|\boldsymbol{\mu}^{j+1} - \boldsymbol{\mu}^j| < \varepsilon$

In [95] it is shown that with a convex objective function and affine constraints the optimal EV charging profile can be found by this method. We will therefore refer to the tariff that results from this algorithm as the ‘optimal tariff’.

6.3.4 Proxies for optimal tariff

The three congestion management mechanisms that we discussed so far should, in theory, all lead to the same optimal EV profile. They have, however, certain practical difficulties associated with their implementation, so we will investigate a number of proxies for the optimal tariff that are simpler and easier to implement. We consider three possible proxies and discuss them in the order of increasing complexity. We add a constant part to all tariffs, including the tariffs described above, in order to make the average tariff equal to 0.04EUR/kWh, which is equal to the current network-related part in the Dutch electricity tariff. This is, however, for the optimization irrelevant since the constant part of the tariff drops out of the optimization objective.

A day-night tariff The simplest time-dependent network tariff is a day-night tariff. In the Netherlands, the night tariff is in effect from 11 PM to 7 AM, so we assume the same period. A second degree of freedom is the price difference between the periods. Here we assume a value of 0.02 EUR/kWh.

This tariff structure has a number of desirable features. Day-night electricity tariffs are already in place in many countries and consumers are therefore familiar with it. In addition, it is transparent for consumers since it is always the same. Furthermore, it does not require network load to be metered or forecast. At most, one might adjust the starting hours of the different tariff periods and the price difference periodically.

A time of use tariff based on historical network load A more differentiated time of use (ToU) tariff would take into account the shape of the network load profile. This varies from day to day, depending on many factors such as the weather, the composition of the loads connected to the network (residential, commercial, etc), type of houses, etc. Ignoring these variations, one could simply take the average load profile over a period in the past and base the tariff on that profile.

The reason for taking the load profile into account is the following: the tariff should be high when network load is high and vice versa. We take a simple approach and scale the load profile (measured in kW) linearly with a conversion factor (unit: EUR/h) to obtain a time-differentiated tariff in EUR/kWh. The value of the conversion factor is chosen such that the average tariff again equals 0.04 EUR/kWh.

This tariff, although a bit more sophisticated, has most of the positive features of the day-night tariff: it is transparent for consumers since it is the same every day and easy to implement (as it does not require an IT infrastructure). In addition, it only requires past network load measurements.

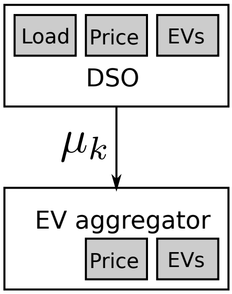
A time of use tariff based on real network load A next step in the complexity of a proxy tariff is to base the tariff on expected real network load. It is the same as the previous tariff, except that now we use the real network load profile, instead of a historic average. This should give a more precise economic signal, but requires more enabling IT infrastructure. The most serious requirement is that now it becomes necessary to forecasted network load, because the tariffs need to be announced ahead of time. How far ahead exactly is a point that deserves further study that we consider outside the scope of this chapter. We emphasize that we assume perfect network load forecasts in our simulations (which we present in the next section). In reality, one needs to find a balance between forecasting as far ahead as possible, which allows consumers to adjust their demand in a timely fashion and accepting larger forecast errors.

This tariff also requires a more sophisticated IT infrastructure, because forecasts need to be announced to the consumers frequently. One can think of a variety of possibilities to do this, ranging from announcements on web pages to dedicated IT systems. We consider discussion on this theme important, but outside our scope. For consumers, this tariff is the least transparent of the proxy tariffs, since it changes every day.

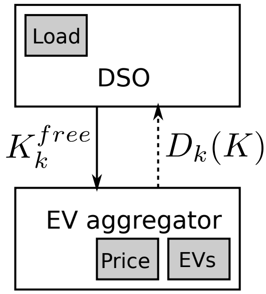
6.3.5 Comparison

Fig. 6.3 schematically shows the four (counting the proxy tariffs as one) different congestion management schemes that have been discussed. The drawings indicate the information flows between the DSO and the aggregator(s). The variables that the stakeholders are required to forecast in the different schemes are indicated as grey boxes. We distinguish between network load (indicated with load), electricity wholesale prices (price) and all EV related information, i.e. planned trips and technical EV parameters, which determine the demand for EV charging.

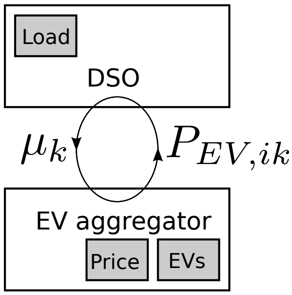
Fig. 6.4 shows the optimal tariff as well as the three proxy tariffs that we consider in this chapter. One observes how the three proxies give quite a strong signal in



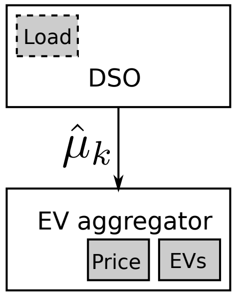
(a) Advance capacity allocation.



(b) Dynamic grid tariff.



(c) Iterative distribution grid capacity market



(d) Proxies for grid tariff

Figure 6.3 – Schematic representation of the different congestion management schemes. μ_k denotes a time varying network tariff , $\hat{\mu}_k$ a proxy network tariff, K_k^{free} available network capacity, $D_k(K)$ a demand function for network capacity at time k and $P_{EV,ik}$ denotes EV load. The gray blocks denote forecasting of information that has to be done by the stakeholders. Arrows denote information flows. Dashed lines mean to indicate that this arrow/block may not be necessary.

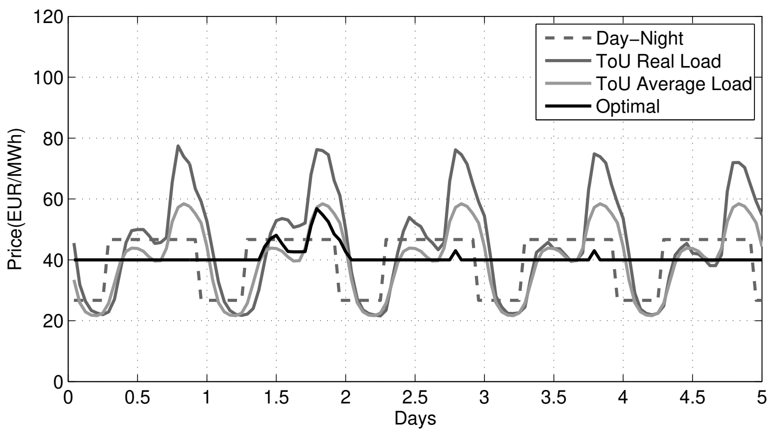


Figure 6.4 – Comparison of the different network tariffs.

comparison with the optimal tariff, which is essentially always constant except when congestion occurs. This observation suggests that the proxies may perform well in terms of reducing the peak load, but will distort the economic signal of the energy prices and therefore result in higher energy costs.

6.4 Results and discussion

We will now discuss the results of the simulations with which we evaluated the various congestion management methods. In the presentation of the results we focus on two output parameters: 1) the peak load, which is a measure of the extent to which the congestion management mechanism was able to prevent congestion and 2) the total costs of charging the EVs, which is measure of the economic efficiency of the congestion management mechanism. The unilaterally determined dynamic grid tariff is not simulated explicitly because of the difficulties of its application in practice. However, the optimal tariff that was found using the iterative grid capacity market can be considered to approximate it closely. In the presentation of the simulation results, the method labeled 'optimal tariff' can hence be considered to represent both the dynamic network tariff from section 6.3.1 and the distribution grid capacity market from section 6.3.3.

6.4.1 Simulation setup

We evaluated the various congestion management mechanisms discussed above with our simulation model. The setup is similar to the one described in section 6.2.3. The network tariffs, both the optimal tariff and those of the proxy methods, are contained in the μ_k term in Eq. 6.3. We emphasize that in the simulations with the network tariffs, we did not include the network constraint (Eq. 6.8) in the optimization. Furthermore, in the simulation of the advance capacity allocation method it was assumed that there was only one aggregator on the network under consideration. Hence, the allocation of the capacity could be done in a straightforward manner by directly including the network constraint 6.8 in the optimization problem. In the algorithm for the iterative grid capacity market, the convergence criterion ε was set to 0.01.

6.4.2 Simulation results

The lower panel of Fig. 6.5 shows the resulting load profiles for the simulated distribution cable for a typical period. One observes several interesting features. Most notably, we see that the dashed lines that correspond to the proxy tariffs *all* show network peaks similar to the flat tariff. These tariffs therefore perform poorly with respect to network peak reduction. Secondly, the load profile resulting from the optimal tariff and the load profile representing the advance capacity allocation method are identical. This shows that both methods indeed converge to the same EV charging profile.

Load profiles for an entire year are commonly summarized in a load-duration curve. The upper panels of Fig. 6.5 show the load duration curves for all mechanisms.

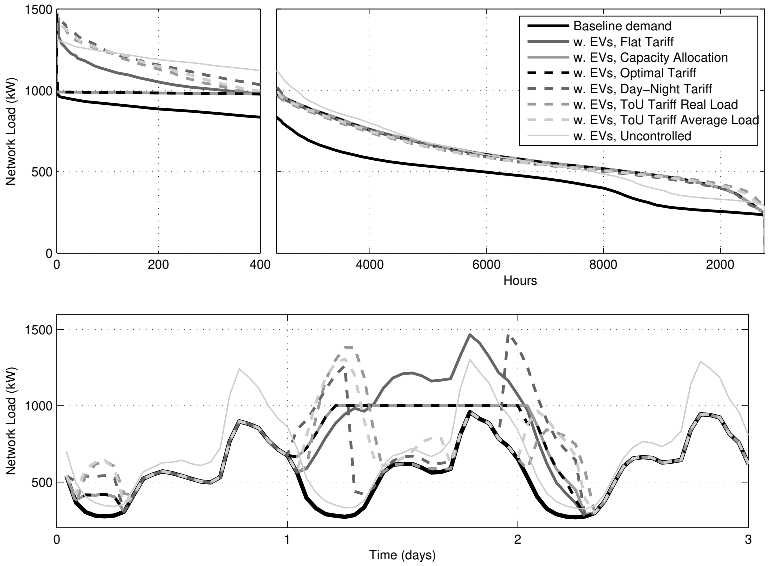


Figure 6.5 – Comparison of the different load profiles. The upper panels shows the yearly load duration curve (a detail of the first part in the left panel) and the lower panel shows a typcial period of three days.

The left side of the figure is an enlargement of the first 400 hours of the full load-duration curve, which is shown on the right. The figure confirms that the load-duration curve that results from an optimal tariff, as obtained through an iterative capacity market, is practically identical to the advance capacity allocation case. We also note how the three proxy tariffs all lead to a higher load peak. The reason is that the proxy network tariffs do not make use of feedback between the network tariff and EV load (like the quadratic term in Eq. 6.3) so, as a result, EV load concentrates in moments with low tariffs. This result is similar to what one observes when the dependence between EV load and the electricity price is not included in a minimum electricity cost formulation, as was e.g. shown in [38].

The second important performance criterion of the different tariffs, in addition to the peak load on the cable, is economic efficiency. This can be evaluated from the total yearly electricity costs for EV charging. We emphasize that these do not contain the network costs. Table 6.1 shows the total yearly energy costs for the EV fleet. We note that the energy costs for a fleet of approximately 500 EVs are 58,600 EUR in case of uncontrolled charging (when EVs do not respond to wholesale prices nor any network tariff signal), whereas the flat tariff with EVs minimizing their costs in response to the wholesale price signal, whithout consideration for grid constraints, yields the lowest cost of 41,900 EUR. Interestingly, the application of an efficient congestion management method causes the charging costs to be only slightly higher (42,100 EUR) than the unconstrained flat tariff case. We draw the important conclusion that the network constraint is a ‘cheap constraint’, much cheaper than investing in the additional network capacity that would be needed to avoid the

Table 6.1 – Comparison of simulation results

Case	Peak demand (MW)	Charging Costs (kEUR)
No EVs	1.00	-
Uncontrolled	1.35	58.6
Flat tariff	1.47	41.9
Advance capacity allocation	1.00	42.1
Optimal tariff	1.00	42.1
Day-night tariff	1.69	49.0
Historic ToU tariff	1.58	49.7
Real ToU tariff	1.55	49.3

congestion. This may not always be the case, but given the fact that we started with a minimally-dimensioned network (just large enough to match current peak demand) and high volumes of RES and EVs, it is likely to be true in many other cases.

We observe that the proxies perform considerably worse with respect to charging costs, approximately 20% higher than in the optimal tariff case. This is due to the fact that the proxy network tariff always distort the electricity price signal, while this is not needed most of the time. Combining the fact that the proxies lead to a higher network peak and higher energy costs, we can only conclude that they do not work. The business-as-usual option (a flat tariff) is even preferable to proxy network tariffs.

6.4.3 Comparison of results to the literature

An assumption that underlies the 'dynamic grid tariff' that was proposed in [91] and also discussed in [92] is that the DSO can accurately forecast the electricity price, network load and EV preferences, and correctly compute the optimal grid tariffs from them. The stochastic, non-linear bi-level optimization problem that is the mathematical formalization of this scheme may actually be very difficult, if not impossible, to solve with acceptable accuracy and computing time. Future research should shed more light on the practical implementation of this. Furthermore, one may question if a DSO should even engage in the forecasting and optimization tasks that are involved with this scheme because they are fundamentally different from his core tasks of network operation and maintenance.

The iterative distribution grid capacity market was described in [90], [92] and [95]. As already pointed out in [92], this approach also creates a large computational and communicative burden for both the DSO and EV aggregator(s). The convergence of this procedure is an issue that is worthwile discussing, as was also done in [95], who illustrated it with a numerical example of a small conceptual system. The system studied in this chapter can be considered somewhat richer (with 25 EVs and a 120 timestep optimization horizon), so it is interesting to evaluate the convergence of the algorithm in this particular setting. In 166 out of the 360 simulations we performed there was grid congestion. Fig. 6.6 shows the distribution of the number of iterations

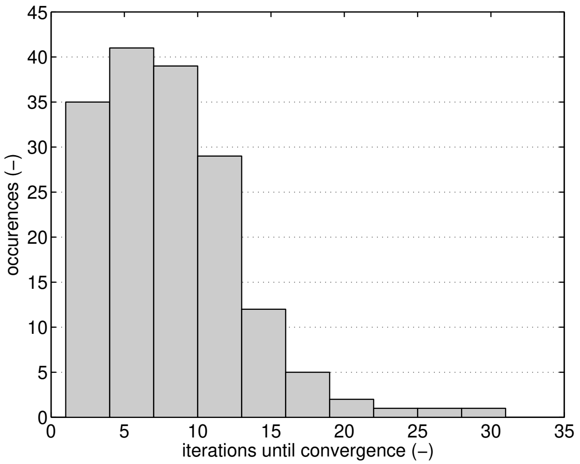


Figure 6.6 – Number of iterations until convergence for the iterative capacity market algorithm.

needed to converge (according to the criterion outlined in section 6.3.3) to a network tariff that solved the congestion. It can be seen that in the majority of the cases the algorithm converges within 10 iterations and the highest number of iterations required to converge was 33. This is in line with [95] who also find convergence after approximately 10 iterations.

The advance capacity allocation method described in this chapter is straightforward if one assumes the presence of a single EV aggregator on each distribution network branch. It seems, however, unlikely but also undesirable from a competition point of view that this is the case. In the case of multiple aggregators, the DSO allocates the free capacity according to some distribution ratio. How this ratio should be chosen in a fair and economically efficient way is an important question. Alternatively, free capacity could be auctioned among the various aggregators who will need to communicate their demand function for network capacity to the DSO at every time step. It is important to mention here again that the free network capacity is not a single quantity but a function of time (the free capacity is given by $K_l - P_{l,k}$). Combined with the inter-temporal constraints associated with the demand response optimization by the EVs, this makes the advance allocation by ex-ante communication of demand complicated. A secondary market in which capacity rights can be traded could prove to be a helpful mechanism in this respect. An allocation based on an off-line computed maximum willingness to pay is another possibility.

The congestion management schemes investigated in this chapter are also interesting in the light of proposed methods for integrating price-responsive energy demand with electricity generation such as the ones discussed by [56]. The main difference in scope is that [56] discusses methods for matching supply and demand of energy whereas we concern ourselves mainly with supply and demand of network capacity. [56] proposes to replace point by point iterations between suppliers and demand of electricity with the exchange of demand functions, which are constructed by varying energy prices uniformly and calculating corresponding values for demand. This approach could also be of interest for the grid capacity market discussed here, but the inter-temporal constraints remain an issue to be investigated further.

6.4.4 Uncertainty

The optimizations that were formulated in the previous sections are all deterministic: all actors had perfect knowledge of future electricity prices, driving behavior and network load. In reality this is not the case and all of the above optimization tasks are questions of decision making under uncertainty. This justifies the question which of the proposed congestion management schemes performs best under the assumption of imperfect information.

A dynamic grid tariff set by the DSO requires forecasts of EV driving schedules, technical EV parameters, electricity prices and inelastic network load, as one can see from the optimization formulation of Eqs. 6.9 to 6.15 and schematically in Fig. 6.3. Therefore many uncertainties enter the problem. Except for network load, it seems difficult for a DSO to forecast these variables since they do not belong to his core business. The distribution grid capacity market appears more promising because it requires actors only forecast variables in their own 'domain', i.e. network load for the DSO and EV parameters and electricity prices for the EV aggregator. The advance capacity allocation mechanism appears to create the smallest forecasting burden: the DSO only needs to forecast network load. Of course, if network capacity is auctioned, the EV aggregator needs to forecast price and EV parameters, but in this case wrong forecasts only lead to economic inefficiency, not to network overloads. Given the low frequency of congestion these costs will probably be limited.

6.4.5 IT infrastructure requirements

Another implementation issue is the requirement for IT infrastructure that is associated with the different schemes. The number of distribution network assets that a DSO handles is typically large. Depending on the method of bookkeeping, or on what network level the congestion management is to be applied, this can be in the orders of tens of thousands of networks. The costs related to the IT infrastructure may therefore be substantial and should be an important criterion in the assessment of different congestion management schemes.

For the ex-ante determined dynamic grid tariff, the IT requirements appear to be rather modest. The main burden in this scheme is for the DSO, who can perform the optimizations 'off line' and only needs to communicate the resulting grid tariff. There does not need to be any communication from aggregator to DSO.

In the case of advance capacity allocation, the DSO communicates the volume of free network capacity to the aggregator(s). In case of only one aggregator, this is everything that is needed, but in case of multiple aggregators they need to send their demand functions to the DSO, who then clears the market. Here, too, the IT requirements do not appear to be excessive, unless, as mentioned in the description of this mechanism, iterations would be required to circumvent the problem of the inter-temporal constraints that make the demand functions in different time-steps dependent on each other.

By far the heaviest requirements on IT infrastructure are associated with the iterative network capacity market. In this scheme, information has to flow iteratively between DSO and aggregator. Also, on the aggregators' side, each iteration requires a new optimization. With large amounts of EVs and especially when stochastic optimization methods are applied, this is a large computational effort in itself. The entire scheme could thus take considerable time, during which information is constantly flowing between the actors.

6.5 Conclusions

This study presents an analysis of methods for managing the congestion of distribution networks that may arise when a large quantity of responsive EV demand reacts to wholesale electricity prices which are influenced by a large share of variable renewable energy sources. We present a mathematical formulation of the EV optimization problem and analyze a number of possible congestion management methods. The most important conclusions from this study can be summarized as follows:

- Variable renewable energy generation weakens the correlation between wholesale electricity prices and electricity demand. As a consequence, large network flows caused by cost-minimizing EV demand may cause distribution network overload.

- The constraint that limited network capacity puts on EV charging has a low cost associated with it. Shifting demand peaks through an optimal congestion management mechanism increases the energy costs of EV charging only marginally.

- Tariffs that are fixed ex ante, based on historic network load profiles, do not solve congestion efficiently and may not be effective at all. They distort the economic signal of the wholesale electricity price, leading to unnecessarily high electricity costs for EV charging. The reason is that network capacity is only a constraint during a limited number of hours per year, while these tariffs force continuous changes in EV charging. Therefore we do not recommend the use of grid tariffs that are fixed ex-ante for managing network congestion that is caused by EVs.

- The unilateral determination of an optimal dynamic grid tariff can be formulated as a non-linear bi-level programming problem where the leader's task is to find a tariff that minimizes the economic distortion of wholesale prices but keeps network loads within bounds. Even in the case of perfect information this is a difficult problem to solve. The additional complexity of uncertainty may render this mechanism infeasible.

- An algorithm for an iterative grid capacity market may solve congestion in an economically efficient way, but its implementation requires frequent exchange of information between DSO and aggregator(s) and therefore poses a heavy computational burden to both the DSO and the EV aggregator.

- Advance capacity allocation is a straightforward method for dealing with network constraints if there is only a single EV aggregator. If more aggregators are active in the same distribution network, a capacity auction could be a possible mechanism, but the existence of inter-temporal constraints for the EV optimization complicates such an auction. Possibly, a secondary market in which capacity rights can be traded among aggregators could contribute to this solution.

We summarize the answer to the question raised in the title of this chapter as follows: due to the limited additional costs of the network constraint on EV charging and the poor performance of grid tariffs that are determined ex ante, an efficient congestion management mechanism will likely be needed for the distribution grid. The introduction of a such a mechanism will postpone or even avoid the need for more costly network capacity upgrades. The design of this mechanism depends on many factors that need to be addressed carefully in future research, for which we recommend a number of possible directions. Most importantly, uncertainties in electricity prices, network load and EV driving schedules need to be taken into account. Furthermore, adding a large share of solar energy would be a valuable addition to the wind-based analysis performed here. Two factors make this particularly interesting: solar energy has a more regular and markedly different timing than wind, and, secondly, it is largely embedded at the distribution level itself. Other important issues to be investigated concern the relations between congestion management on the one hand and investment in new distribution assets and capital cost recovery on the other hand. Another topic that deserves more attention is the question how to embed the distribution grid congestion management mechanisms in the new energy market designs as discussed in [56]. Finally, we recommend more detailed studies of the exact design of the different congestion management mechanisms. The specifics of capacity allocation by auctioning, demand functions for network capacity, bids representening willingness to pay, the iterative grid capacity market, etc, should be investigated in such studies.

Chapter 7

A refined view on electric vehicle charging

In this chapter we aim to connect the individual elements provided by chapters 4, 5 and 6. Those chapters not only dealt with several aspects of the role of EVs in power systems, but there were also different assumptions and/or viewpoints regarding the EV charging process. Table 7.1 lists the most important assumptions concerning the EV charging formulation. The main differences in modeling assumptions are the availability of the EVs for charging, inter-temporal constraints in the power plant scheduling and differences in the optimization objectives and the optimization horizon.

Chapter 6 already deals with the combination of the optimization objectives related to distribution grid capacity and charging costs based on wholesale prices with a control horizon of 5 days. The main difference between chapter 5 and chapter 6 is that in the former, EVs were taken into account in the generation scheduling problem from a centralized viewpoint, where in the latter, EVs react to wholesale prices that reflect marginal generation costs. To what extent, and under what conditions the decentralized and centralized formulations lead to the same outcomes in terms of EV dispatch is therefore investigated in this chapter. Furthermore, the sensitivity to

Table 7.1 – Overview of most important modeling assumptions in different chapters

Chapter	EV charging availability	Optimization objective	Optimization horizon
4	Charging is assumed to be done only at home, after the last arrival	Minimize network load. Centralized formulation	One day
5	EVs are assumed to be always available for charging	Minimize generation costs. Centralized formulation. Full unit commitment.	Five days
6	EVs are assumed to be always available for charging	Minimize EV charging costs within network limits. Decentralized formulation	Five days

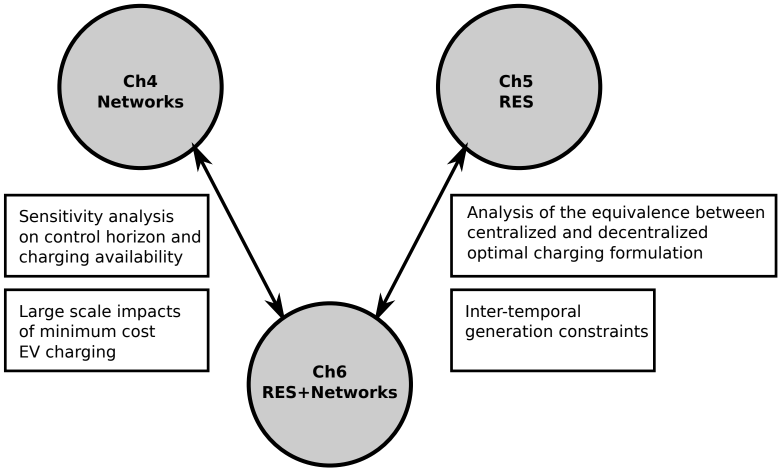


Figure 7.1 – Schematic representation of the elements discusses in this chapter and their relation with previous chapters.

the inter-temporal constraints that are taken into account in the unit commitment problem of chapter 5 is analyzed.

The main difference between chapter 4 and 6 is that in the latter, EVs are assumed to be always available for charging and they optimize over a horizon of five days, whereas in the first EVs charge only at home and require a full battery every day. A sensitivity analysis on these two aspects is performed to shed more light on them. Fig. 7.1 shows schematically the relations between the chapters and the main research elements investigated in this chapter that provide the link between them. We begin this chapter by analyzing the differences between charging from a centralized viewpoint (a social planner) and a decentralized viewpoint of aggregators reacting to electricity wholesale prices.

7.1 Equivalence of centralized and decentralized demand scheduling

In chapter 5 the scheduling of EV demand was done from a centralized point of view: one entity scheduled the EV demand to minimize the total generation costs of the entire system. In chapter 6, on the other hand, a decentralized approach in which EVs were only reacting to wholesale electricity prices was taken. Chapter 4 had yet a somewhat different approach because there was EV charging was formally not considered as optimization problem, but the philosophy of a DSO controlling EV charging can also considered to be a centralized approach. The question arises to what extent the centralized and decentralized approaches are equivalent. We approach this question first by considering a simple conceptual system. After that we present simulation results of a case study based on the Netherlands.

7.1.1 Theoretical analysis of EV dispatch

In this section we use a number of basic concepts from mathematical optimization theory that can be found in standard textbooks like [35] and [37].

Centralized EV dispatch Consider a power system with one generator with a strictly convex cost curve $C(P_G)$. This is a conceptualization of the situation where a finite number of generating units with different marginal cost curves serve electricity demand. There are two time-steps with different electricity demand P_{D1} and P_{D2}. The basic economic dispatch problem is to meet the demand for the lowest generation costs. The mathematical formulation reads:

$$\min_{P_{G1},P_{G2}} C(P_{G1}) + C(P_{G2}) \tag{7.1}$$

$$\text{s.t.} \quad P_{G1} = P_{D1} \tag{7.2}$$

$$P_{G2} = P_{D2} \tag{7.3}$$

This problem can be solved by forming the Lagrangian and differentiating with respect to P_{G1} and P_{G2} and the Lagrange multipliers λ_1 and λ_2 that correspond to constraints 7.2 and 7.3. The latter two denote the marginal system cost (and hence electricity price) at the two time-steps. The solution to this problem is trivial since it is immediately dictated by the constraints.

Now consider that there is an extra portion of, say, EV related electricity demand B, but it can be scheduled in a flexible way between time-step one and two. This problem reads:

$$\min_{P_{G1},P_{G2},P_{EV1},P_{EV2}} C(P_{G1}) + C(P_{G2}) \tag{7.4}$$

$$\text{s.t.} \quad P_{G1} = P_{D1} + P_{EV1} \qquad :\lambda_1 \tag{7.5}$$

$$P_{G2} = P_{D2} + P_{EV2} \qquad :\lambda_2 \tag{7.6}$$

$$P_{EV1} + P_{EV2} = B \qquad :\kappa \tag{7.7}$$

The Lagrangian associated with this problem reads:

$$\begin{aligned} &\mathcal{L}(P_{G1}, P_{G2}, P_{EV1}, P_{EV2}, \lambda_1, \lambda_2, \kappa) = C(P_{G1}) + C(P_{G2}) \\ &- \lambda_1(P_{G1} - P_{D1} - P_{EV1}) - \lambda_2(P_{G2} - P_{D2} - P_{EV2}) \\ &- \kappa(P_{EV1} + P_{EV2} - B) \end{aligned} \tag{7.8}$$

larger and the first-order necessary optimality conditions are given by:

$$\frac{\partial C}{\partial P_{G1}} - \lambda_1 = 0 \tag{7.9}$$

$$\frac{\partial C}{\partial P_{G2}} - \lambda_2 = 0 \tag{7.10}$$

$$\lambda_1 - \kappa = 0 \tag{7.11}$$

$$\lambda_2 - \kappa = 0 \tag{7.12}$$

together with the constraints 7.5, 7.6 and 7.7. From this we find readily that $\frac{\partial C}{\partial P_{G1}} = \frac{\partial C}{\partial P_{G2}}$. The assumption of strict convexity implies that the derivative evaluated at two points can only be equal if those points are equal. This leads to the following solution:

$$\lambda_1 = \lambda_2 = \kappa \tag{7.13}$$

$$P_{G1} = P_{G2} = \frac{1}{2}B + \frac{1}{2}(P_{D2} + P_{D1}) \tag{7.14}$$

$$P_{EV1} = \frac{1}{2}B + \frac{1}{2}(P_{D2} - P_{D1}) \tag{7.15}$$

$$P_{EV2} = \frac{1}{2}B - \frac{1}{2}(P_{D2} - P_{D1}) \tag{7.16}$$

The flexible demand is thus scheduled such that the total demand is exactly equal in both time-steps. This makes sense in the light of the convex nature of the cost function. Fig. 7.2 shows a conceptual representation of this problem and the solution. When a non-negativity constraint is added for the EV demand, we find by writing the Karush-Kuhn-Tucker (KKT) conditions[1] the following solutions. In the case that $B > P_{D2} - P_{D1}$ we have

$$P_{G1} = P_{G2} = \frac{1}{2}B + \frac{1}{2}(P_{D2} + P_{D1}) \tag{7.17}$$

$$P_{EV1} = \frac{1}{2}B + \frac{1}{2}(P_{D2} - P_{D1}) \tag{7.18}$$

$$P_{EV2} = \frac{1}{2}B - \frac{1}{2}(P_{D2} - P_{D1}) \tag{7.19}$$

and when $B \leq P_{D2} - P_{D1}$

$$P_{G1} = B + P_{D1} \tag{7.20}$$

$$P_{G2} = P_{D2} \tag{7.21}$$

$$P_{EV1} = B \tag{7.22}$$

$$P_{EV2} = 0 \tag{7.23}$$

In the first case the solution is the same as in the case without inequality constraints, in the second case all flexible demand is scheduled in the time-step with the lowest inelastic demand.

Decentralized EV dispatch In the decentralized demand dispatch, flexible demand reacts to an electricity price. The relation between electricity price and demand is essentially given by the marginal cost curve of electricity generation, which, in our conceptual representation, would be simply the derivative of the curve $C(P_G)$ at a given demand P_D. We thus define the EV load dependent price as:

$$C'(P_{EV}) = \left.\frac{dC}{dP_G}\right|_{P_G = P_D + P_{EV}} \tag{7.24}$$

[1]The KKT conditions are necessary conditions for the optimal solution of non-linear optimization problems with inequality constraints. Although in most cases a solution can not directly be derived from them, they do often provide useful insights of the solution.

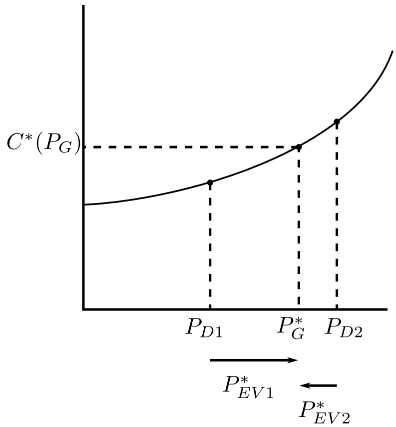


Figure 7.2 – Schematic representation of the economic dispatch with flexible demand. The flexible demand is shifted such that the demand at both time-steps is equal. Note that P_{EV2}^* is negative in this example.

where the load balance constraint $P_G = P_D + P_{EV}$ has been used to express the electricity price as a function of demand. In this case the optimization problem is to minimize the charge costs which, for each time-step, are given by the product of the volume and price. It reads:

$$\min_{P_{EV1},P_{EV2}} \quad C'(P_{EV1})P_{EV1} + C'(P_{EV2})P_{EV2} \tag{7.25}$$

$$\text{s.t.} \quad P_{EV1} + P_{EV2} = B \qquad :\kappa \tag{7.26}$$

The Lagrangian of this problem is given by:

$$\begin{aligned}\mathcal{L}(P_{EV1}, P_{EV2}, \kappa) = C'(P_{EV1})P_{EV1} + C'(P_{EV2})P_{EV2}\\ - \kappa(P_{EV1} + P_{EV2} - B)\end{aligned} \tag{7.27}$$

The first-order optimality conditions are found by differentiating Eq. 7.27 with respect to the optimization variables. Using the chain rule for derivatives we find:

$$\begin{aligned}\left.\frac{\partial C'}{\partial P_{EV1}}\right|_{P_{D1}+P_{EV1}} P_{EV1} + C'(P_{EV1}) - \kappa = 0\\ \left.\frac{\partial C'}{\partial P_{EV2}}\right|_{P_{D2}+P_{EV2}} P_{EV2} + C'(P_{EV2}) - \kappa = 0\end{aligned} \tag{7.28}$$

Without an exact expression for $C(P_G)$ we cannot derive a meaningful solution from the above formulation. However, if we compare Eqs. 7.9 to 7.12 with Eq. 7.28 we notice the extra term with second derivative of the cost curve $C(P_G)$. Only if this term is zero, the two conditions are identical, but in this case there is no unique solution to the problem since the price is constant and equal for both time-steps. Graphically we interpret this problem as depicted in Fig. 7.3. The sum of grey areas denote the objective functions to be minimized. If we compare this with

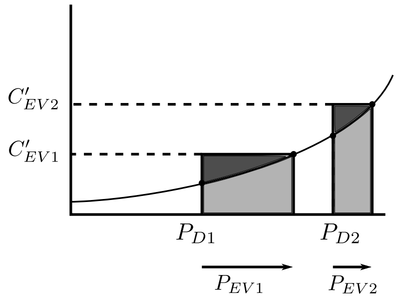


Figure 7.3 – Schematic representation of the decentralized dispatch of flexible demand. The total grey area is represents the costs to be minimized. The dark grey area denote the difference with the centralized formulation.

the centralized formulation and recall that the price at a certain electricity demand $C'(P_D)$ was the derivative of the cost function $C(P_G)$, we note that the dark grey areas are exactly the difference with the objective function in that formulation, which are represented by the integral of $C'(P_D)$ (the light grey area). This also explains why the difference in the two formulations becomes smaller as the second derivative of $C(P_G)$ approaches zero, because then the dark grey areas become smaller as well.

An example with a quadratic cost function Before moving on to the case with multiple EV aggregators, we consider it to be instructive to first evaluate the previously treated general cases with an exact expression for the cost curve $C(P_G)$. To this end we define a quadratic function:

$$C(P_G) = \frac{1}{2}aP_G^2 + bP_G + c \tag{7.29}$$

Furthermore we have again the inelastic demand in the two time-steps P_{D1} and P_{D2} and the energy constraint on the flexible demand $P_{EV1} + P_{EV2} = B$. Working out the solutions in the centralized case yields the solution already found in the general case which we repeat here for convenience

$$P_{EV1} = \frac{1}{2}B + \frac{1}{2}(P_{D2} - P_{D1}) \tag{7.30}$$

$$P_{EV2} = \frac{1}{2}B - \frac{1}{2}(P_{D2} - P_{D1}) \tag{7.31}$$

In the decentralized case we now have

$$C'(P_{EV}) = a(P_D + P_{EV}) + b \tag{7.32}$$

so the optimization problem reads:

$$\min_{P_{EV1},P_{EV2}} (a(P_{D1} + P_{EV1}) + b)P_{EV1} + (a(P_{D2} + P_{EV2}) + b)P_{EV2} \tag{7.33}$$

$$\text{s.t.} \quad P_{EV1} + P_{EV2} = B \tag{7.34}$$

We can use the constraint 7.34 to eliminate P_{EV} and then differentiate the resulting expression with respect to P_{EV1} to find a condition for the optimum:

$$4aP_{EV1} + a(P_{D1} - P_{D2}) - 2aB = 0 \tag{7.35}$$

which yields the following solution:

$$P_{EV1} = \frac{1}{2}B + \frac{1}{4}(P_{D2} - P_{D1}) \tag{7.36}$$

$$P_{EV2} = \frac{1}{2}B - \frac{1}{4}(P_{D2} - P_{D1}) \tag{7.37}$$

We note that this solution indeed differs from the one found in the centralized case.

Decentralized EV dispatch with multiple aggregators In the preceding sections we compared a centralized demand scheduling entity with an aggregator who schedules demand on the base of expected prices. In the latter case, however, the aggregator scheduled all demand and was clearly not a price taker, because the price dependency was explicitly taken into account. Now we consider the case where there is not a single aggregator anymore, but a second one with an equal amount of flexible demand. Both aggregators will aim to minimize the charge costs, anticipating on the behavior of the other. The resulting situation can be considered a Cournot model of a duopoly, see e.g. [18]. We split the flexible demand exactly in half for each aggregator, so $P_{EV1} + P_{EV2} = B/2$ and $\hat{P}_{EV1} + \hat{P}_{EV2} = B/2$, where we labeled the second aggregators demand with $\hat{P}$.

We use the same quadratic expression Eq. 7.29 for the cost function. Furthermore, for notational convenience we define $c_1 = aP_{D1} + b$ and $c_2 = aP_{D2} + b$ so that we can write for the first aggregators objective function in the duopoly:

$$\min_{P_{EV1}, P_{EV2}} \; (c_1 + aP_{EV1} + a\hat{P}_{EV1})P_{EV1} + (c_2 + aP_{EV2} + a\hat{P}_{EV2})P_{EV2} \tag{7.38}$$

$$\text{s.t.} \quad P_{EV1} + P_{EV2} = B/2 \tag{7.39}$$

By using the same procedure as before, i.e. eliminating P_{EV2} and $\hat{P}_{EV2}$ using the constraints and setting the derivative with respect to P_{EV1} to zero, we find the following condition for the maximum:

$$P_{EV1} = \frac{c_2 - c_1}{4a} + \frac{3}{4}\frac{B}{2} - \frac{1}{2}\hat{P}_{EV1} = f_1(\hat{P}_{EV1}) \tag{7.40}$$

We find a similar expression for the second aggregator:

$$\hat{P}_{EV1} = \frac{c_2 - c_1}{4a} + \frac{3}{4}\frac{B}{2} - \frac{1}{2}P_{EV1} = f_2(P_{EV1}) \tag{7.41}$$

For the Nash equilibrium[2] it holds that

[2]In the Nash equilibrium none of the two competing aggregators would benefit from changing its decision unilaterally. This is where the Cournot duopoly should eventually converge to.

$$P^*_{EV1} = f_1(\hat{P}^*_{EV1}) \tag{7.42}$$
$$\hat{P}^*_{EV1} = f_2(P^*_{EV1}) \tag{7.43}$$

To solve this system, we write in more compact form

$$P^*_{EV1} = C - \frac{1}{2}\hat{P}^*_{EV1} \tag{7.44}$$
$$\hat{P}^*_{EV1} = C - \frac{1}{2}P^*_{EV1} \tag{7.45}$$

which leads, after some rewriting to the solutions:

$$P^*_{EV1} = \hat{P}^*_{EV1} = \frac{2}{3}C = \frac{1}{2}\frac{B}{2} + \frac{2}{3}\left(\frac{c_2 - c_1}{4a}\right) = \frac{1}{2}\frac{B}{2} + \frac{1}{6}(P_{D2} - P_{D1}) \tag{7.46}$$

In a straightforward manner we can extend the analysis for N aggregators and find for the demand of aggregator i:

$$P^{(i)*}_{EV1} = \frac{1}{2}\frac{B}{N} + \frac{1}{2}\frac{P_{D2} - P_{D1}}{N+1} \tag{7.47}$$

To compare the total EV demand with the case where there was only a single aggregator, we now sum the EV demand in the first time-step of the all aggregators and find for the aggregated EV demand:

$$P_{EV1} = \frac{1}{2}B + \frac{1}{4}(P_{D2} - P_{D1}) \qquad \text{for one aggregator} \tag{7.48}$$
$$P_{EV1} = \frac{1}{2}B + \frac{1}{3}(P_{D2} - P_{D1}) \qquad \text{for two aggregators} \tag{7.49}$$
$$P_{EV1} = \frac{1}{2}B + \frac{1}{2}\frac{N}{N+1}(P_{D2} - P_{D1}) \qquad \text{for } N \text{ aggregators} \tag{7.50}$$

The expression for the demand in the second time-step follow from the constraints that we used to eliminate the P_{EV2} variable.

The interpretation of this result is that for a large number of aggregators the last expression approaches the solution of the centralized case and the flexible demand is dispatched in an manner that maximizes social welfare. This is a result that could be expected on the basis of the economic intuition that if the number of market players is very large, they are not able to benefit from influencing prices.

7.1.2 Simulations comparing centralized and decentralized EV dispatch

The previous section presented a theoretical analysis on centralized vs. decentralized demand dispatch in a simple conceptual system. We now repeat the analysis by comparing simulations in a model representing the Netherlands. The decentralized model is similar to the one used in chapters 2 and 6 and described in [38] with the main difference that we now allow for multiple aggregators. Each aggregator performs the following optimization:

$$\min_{P_{EV,ik}} \sum_{k=1}^{N_k} \alpha_k P_{EV,k} + \beta P_{EV,k}^2 \tag{7.51}$$

$$\text{s.t.} \quad P_{EV,k} = \sum_{i \in EV_j} P_{EV,ik} \qquad \forall k \tag{7.52}$$

$$P_{EV_{min},i} \leq P_{EV,ik} \leq P_{EV_{max},i} \qquad \forall i,k \tag{7.53}$$

$$E_{EV_{min},i} \leq E_{EV,ik} \leq E_{EV_{max},i} \qquad \forall i,k \tag{7.54}$$

$$E_{EV,ik+1} = E_{EV,ik} + \eta_c P_{EV,ik} - d_{ik} \qquad \forall i,k \tag{7.55}$$

Here EV_j denotes the subset of vehicles belonging to aggregator j. Before performing this optimization, each aggregator updates the electricity price parameters α_k and β by including the demand of the other aggregators of the previous iteration.

$$\alpha_k = \lambda(\overline{P_{D0} + \hat{P}_{EV}}) + \lambda'(\overline{P_{D0} + \hat{P}_{EV}})(P_{D0,k} + \hat{P}_{EV,k} - (\overline{P_{D0} + \hat{P}_{EV}})) \tag{7.56}$$

$$\beta = \lambda'(\overline{P_{D0} + \hat{P}_{EV}}) \tag{7.57}$$

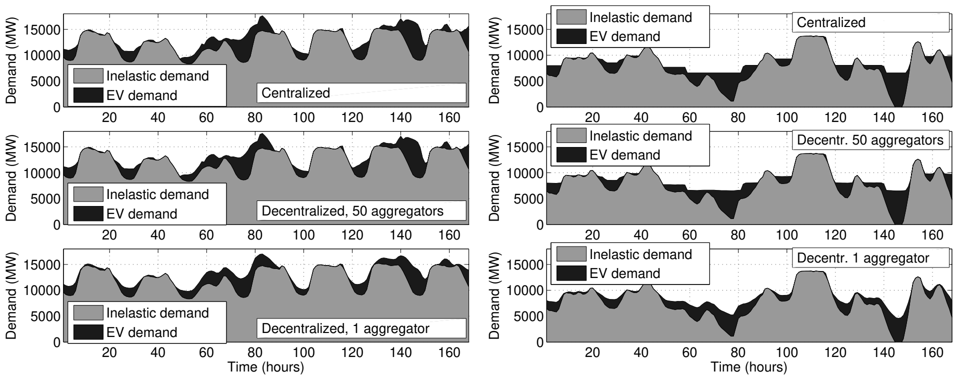
where $\hat{P}_{EV,k}$ denotes the anticipated EV demand of all other aggregators, $P_{D0,k}$ denotes the residual electricity demand (demand minus wind power), and the over-bar denotes an average over the period of optimization. Within one iteration all aggregators perform the above optimization. In the first iteration the demand of all aggregators is set to zero, so all aggregators react on the same electricity price. With this procedure we expect to reach a Nash equilibrium after several iterations.

For reasons of comparison it is instructive to treat the centralized version first. In this formulation it is the task of a single entity to schedule all EV demand such that total *generation* costs are minimized, whereas in the decentralized version *charging* costs are minimized. In the above QP formulation, we have linearized the price around the average demand, using the supply curve that was shown in Fig. 2.17. Since price reflects the supply curve (the marginal generation costs), the total or cumulative generation costs are given by the integral of the supply curve, see also subsection 7.1.1 on the conceptual system. For a linearized supply curve this results in a quadratic formulation of the objective function:

$$\min_{P_{EV,k}} \sum_{k=1}^{N_k} \alpha_k P_{EV,k} + \frac{1}{2} \beta P_{EV,k}^2 \tag{7.58}$$

The difference with the objective function in the decentralized version (Eq. 7.51) is the factor $\frac{1}{2}$ in the quadratic term[3].

[3]This formulation is based only on the marginal costs and effectively ignores inter-temporal constraints of all generation units. In the next section it is shown that this leads to only slightly different EV demand profiles compared to the case with inter-temporal constraints.

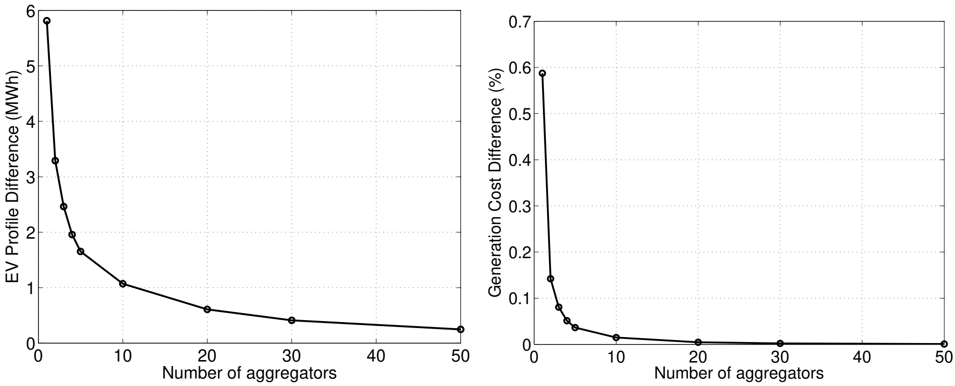


(a) Demand and EV demand (b) Residual demand and EV demand

Figure 7.4 – Comparison between the dispatched EV load in the centralized case and the decentralized cases with 50 and 1 aggregator. Simulations with 15GW wind and 50% EV penetration.

Fig. 7.4 shows a comparison between the centralized formulation (Eq. 7.58) and the decentralized formulation (Eq. 7.51) with 1 aggregator and with 50 aggregators. One clearly observes that the EV demand in the centralized version is practically identical to the case with many aggregators. This confirms the intuition that when EV aggregators are too small to influence market prices, the EV demand will converge to the social optimum. In the case with a single aggregator, however, we observe a somewhat different EV demand profile. One distinguishes the same feature as in the conceptual example of the previous section: a single aggregator benefits from scheduling a part of the demand in periods with higher prices. This rather counter-intuitive notion can be understood by realizing that an extra price is paid for a small portion of the demand, but as a consequence, a lower price is paid for a much larger portion of the demand. Fig. 7.3 illustrates this effect schematically. Fig. 7.4(b) furthermore shows how in the socially optimal cases (the top two figures) the EV demand is scheduled in such a way that the residual demand, and hence the system marginal cost, tends to become equal between different time-steps - an effect usually referred to as 'valley filling'. This was also shown in the conceptual analysis from subsection 7.1.1.

To get some more insight in the influence of the amount of aggregators, Fig. 7.5(a) shows the difference between the centralized (socially optimal) EV dispatch and the decentralized EV dispatch as a function of the number of aggregators. The difference indicates the summed RMS difference between the profiles for a given week. As expected, we see the difference approaches zero for a large number of aggregators. The initial decline is quite fast, indicating that even a small number of aggregators leads to a significant improvement of the EV demand profile. The extra generation costs due to the non-optimal dispatch of the EVs are shown in Fig. 7.5(b). It can be seen that even in the case with a single aggregator scheduling all EV demand, the extra generation costs are quite modest. The cost difference falls very



(a) Energy profile difference (b) Generation cost difference

Figure 7.5 – Difference between the centralized EV profile and the combined EV profile of all aggregators as a function of the number of aggregators. The energy profile difference is the summed absolute difference between the profiles for a week. The generation costs difference are the extra generation costs for this week compared to the centralized case.

rapidly towards zero, once again indicating that even a small number of aggregators is sufficient for an efficiently working demand response market. It should of course be noted that these numbers are based on the residual demand and the supply curve shown in Fig. 2.17. One could speculate that in real systems there are more volatile electricity prices due to the inter-temporal effects. As noted earlier in chapter 2, in Denmark, for example, negative wholesale prices have been observed and this is a phenomenon that our model of the electricity price is unable to capture.

Finally, we look at the number of iterations needed to converge to a Nash equilibrium. Fig. 7.6 shows the difference in energy profiles as a function of the number of iterations. We recall that in the first iteration, the other aggregators demand was assumed to be zero, so all aggregators reacted to the same electricity price that did not include any EV load. In the subsequent iterations, each aggregator added the combined EV demand of all the aggregators to the electricity demand and updated the electricity prices accordingly. We observe that the Nash equilibrium is reached already after a few iterations. When a low amount of aggregators is present, the equilibrium is approached more slowly.

As a final remark, we note that it is interesting to conclude that dispatchable demand can actually offer a possibility for market parties represting only demand and no generation to exert market power. Usually, demand response is seen as a remedy against market power exerted by generators, see e.g. [96]. This is still true, of course, since the flexible demand adjusts itself to avoid price peaks. But when the number of aggregators is very small, the resulting demand profile does not exactly match the social optimum.

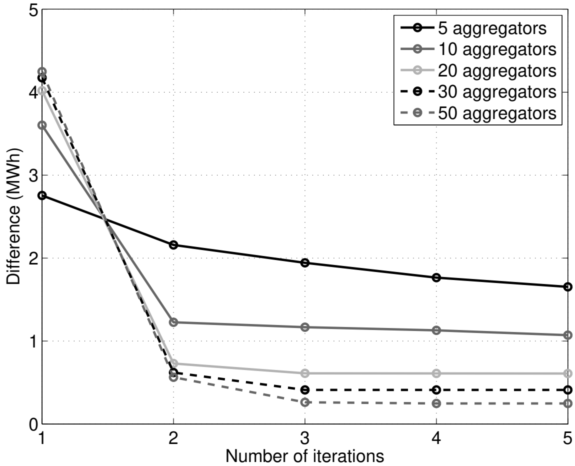


Figure 7.6 – Difference between the centralized EV profile and the combined EV profile of all aggregators as a function of the iteration.

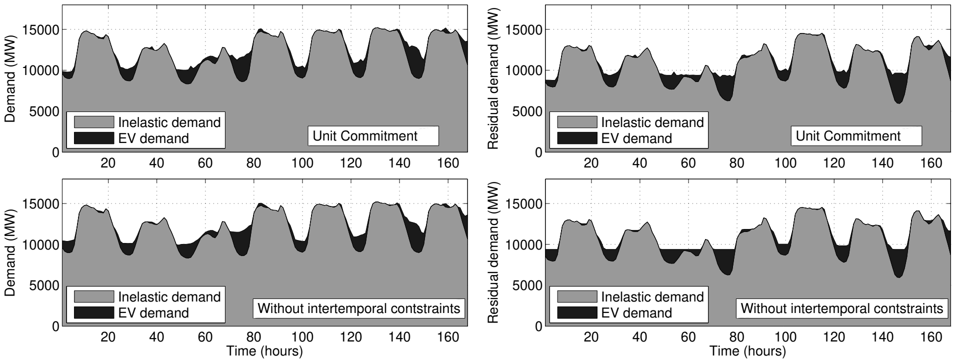
7.2 Sensitivity analysis

7.2.1 Inter-temporal generation constraints

In the previous section we compared centralized and decentralized scheduling of EV demand. Minimizing generation costs in the centralized situation was, however, solely based on the combined marginal cost curve of all power plants and ignored inter-temporal constraints such as start-up costs, ramping rates and minimum power output levels. Therefore we compare in this section the cases of a unit commitment model that takes all this into account with the simplified version ignoring the inter-temporal constraints. The unit commitment (UC) model is described in chapter 5, but this time we use Dutch power plant data that is based on [97]. We recall that the UC model is a mixed-integer *linear* programming model, which means that we assume constant efficiencies for the generation units, whereas a more sophisticated version could include more detailed efficiency curves. The model without inter-temporal constraints is given by Eqs. 7.58 with the usual EV constraints 7.52 to 7.55. In this section we also compare situations with a different amount of installed wind power and a different EV penetration degree.

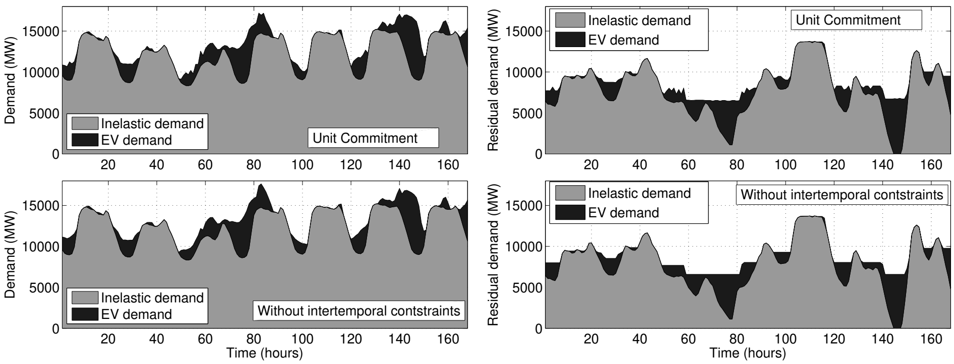
Fig. 7.7 shows the dispatch profiles for the UC model and the model without inter-temporal constraints in the case with 5 GW of installed wind capacity and 25% EV penetration. It can be seen that the differences are small. Part of the difference can be explained by the fact that in the UC model the generation units have constant marginal costs, so in this formulation it does not matter if a unit is generating at, say 40% or 100% of its output. Because of this, we observe a somewhat less smooth EV profile. Furthermore, we note that EV demand is scheduled almost exclusively in the night hours when electricity demand is low.

Fig. 7.8 shows the same plots, but now for a situation with 15 GW of installed



(a) Demand and EV demand (b) Residual demand and EV demand

Figure 7.7 – Comparison between the dispatched EV load in the centralized case and the decentralized case. Simulations with 5GW wind and 25% EV penetration.



(a) Demand and EV demand (b) Residual demand and EV demand

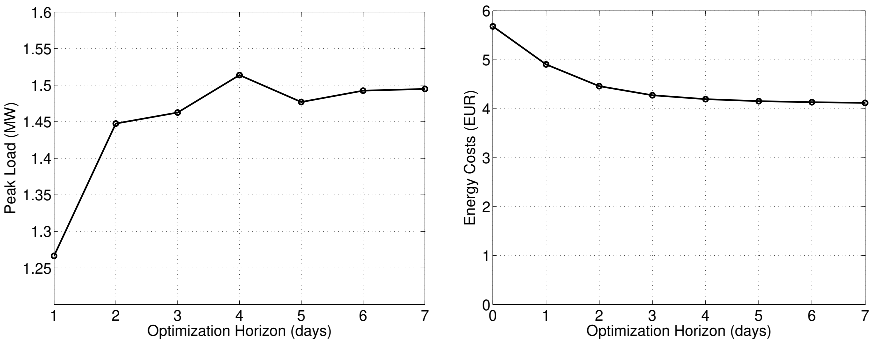
Figure 7.8 – Comparison between the dispatched EV load in the centralized case and the decentralized case. Simulations with 15GW wind and 50% EV penetration.

wind capacity and 50% EV penetration. Once again, the differences between the UC model and the simplified merit order dispatch are small. Moreover, a noteworthy observation is that in this case EV demand is actually scheduled at the system peak, which leads to a significant increase of the peak demand, as can be seen in Fig. 7.8(a). One can readily understand this by looking at Fig. 7.8(b) which shows the residual demand, given by the electricity demand minus wind generation. When wind power is sufficiently high, the actual minimum of residual demand can occur at the peak load hours. This effect, and its consequences for the distribution networks have been discussed as well in chapter 6. These figures show it in much more instructive way though, and they demonstrate that the effect also occurs when considering inter-temporal constraints of electricity generation. It can therefore not be attributed to the simplified electricity price model based on the merit order that we used in chapter 6.

7.2.2 Influence of the forecast horizon

The benefits of a flexible electricity demand are for a large part due to the ability to await favorable conditions (e.g. low prices or low network load) to consume electricity. In the cases that have been treated in this thesis so far, in particular the minimization of charging costs based on wholesale prices, the optimization horizon was set to 5 days. This effectively allowed the EVs to postpone charging up to 5 days to anticipate the low price periods. This, as we saw, lead to large financial benefits in terms of lower energy prices, but also high peaks in network demand because, effectively, the demand of 5 days worth of EV charging is squeezed in a much smaller period. The question thus arises to what extent the energy costs and network peaks are dependent on the horizon over which the optimization is performed. In particular, one could argue that a smaller optimization period would lead to much smaller peaks in the networks, especially since we impose the constraint that all EV batteries have to be full at the end of the optimization period so all energy consumed by EVs on a day has to be recharged the same day. The extreme case of this question has already been considered in the form of the uncontrolled charging scenario, since these can be considered to represent the case with the lowest possible flexibility in charging.

Fig. 7.9(a) shows how the peak network demand (EV demand plus inelastic demand) depends on the control horizon. The same setting was used as described in chapter 6, i.e. a network with approximately 1000 households and 500 EVs, reacting to the electricity wholesale prices based on 15GW installed wind capacity in the Netherlands. Note that we performed simulations spanning a whole year, so the peak demand refers to the highest peak of the year. We observe that, indeed, for an optimization horizon of one day, the network peak is markedly lower. For an optimization period of 2 days the peak increases sharply and there is only little difference for an even longer optimization horizon. It is also interesting to see that the highest peak actually occurs for a horizon of 4 days, and not for 7 days, the longest period we considered. We hypothesize that this is due to the fact that for a very long optimization horizon, another period with low prices might actually enter the horizon and the EV demand can be divided over the two low price periods



(a) Network peak load

(b) Energy costs

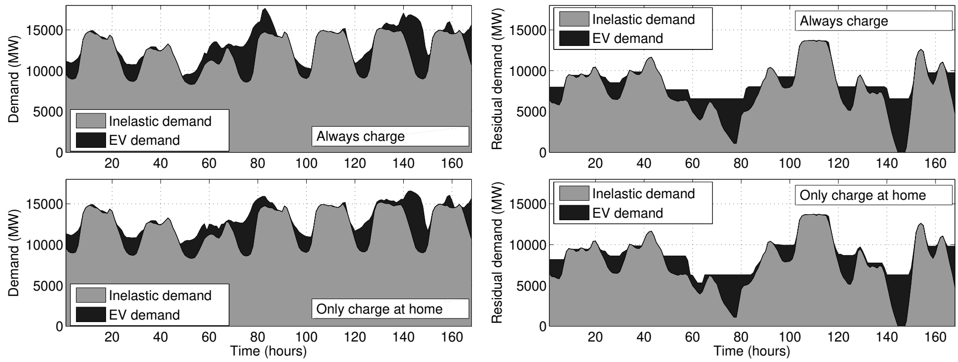
Figure 7.9 – Sensitivity of peak load of combined controllable EV demand and inelastic demand (a) and charging energy costs (b) as a function of the control horizon of the EVs. In the right figure, a control horizon of 0 days denotes the uncontrolled charging profile.

instead of 'squeezing' all the demand in the single low price period.

Given the much lower network peak in the case with a one day optimization horizon, one could argue that the existence of, say, a day ahead gate closure time of markets for (flexible) electricity demand would enforce EVs to plan within this horizon. As a result, the distribution grid congestion issue that would result would be much less severe. We deem this incorrect, however. There is (and should be) no rule or law that forbids market parties to look ahead and plan further than cleared day-ahead prices. Especially in systems with a high RES penetration, we feel that it will actually become increasingly important to look ahead multiple days, in anticipation of high wind or solar periods.

Fig. 7.9(b) shows how energy costs for EV charging depend on the control horizon. Again, energy costs refer to the annual energy costs, since we simulated a whole year. Here, a horizon of 0 days denotes the uncontrolled scenario (charging immediately after arrival at home). We observe that, as expected, the energy costs decrease monotonically as a function of the control horizon. After approximately 3-4 days the effect more or less saturates. This 3 to 4 day period is interesting in the light of the typical battery size of 24 kWh (that was used in our model) in combination with the average daily driving distance of 35 km/day (equivalent with 7 kWh/day), because those numbers imply a timescale of approximately 3.5 days associated with the flexibility in the charging process. This time reflects how long the average driver can postpone charging. This timescale seems to be well reflected in Fig. 7.9(b). One could speculate that for larger EV battery sizes or for stand-alone grid storage systems there would be more value associated with looking even further ahead.

Fig. 7.9(b) is also interesting in the light of predictability of wind driven electricity prices. Reasonably accurate forecasts up to a few days ahead are feasible, so it seems that wind forecast errors would not severely undermine the potential of demand response of EVs.



(a) Demand and EV demand (b) Residual demand and EV demand

Figure 7.10 – Comparison of EV demand profiles between the case where EVs are always able to charge and the case where only charging at home is possible.

7.2.3 Influence of charging availability

In all EV charge optimization problems we have considered so far, we assumed that EVs were always available for charging. In the distribution network analysis from chapter 4 though, we assumed that EVs were only charged at home, after the last arrival of the day. We will therefore consider what the effect of the more limited availability for charging is on the cost minimizing charge strategies.

We expect two counter-acting mechanisms to influence the results in terms of the height of the network peak. On the one hand, one could reason that a more limited charging availability would lead to higher peaks, since the same amount of energy for all EVs has to be charged in a smaller time frame. On the other hand, network peaks could turn out to be lower, since some EVs might already be done charging when others arrive. This 'randomness' is also the reason that the uncontrolled charging profiles have a lower combined peak than the cost minimizing charge strategy.

To model the limited charging availability we simply add the following constraint to the usual EV constraints (Eqs. 7.52 to 7.55):

$$P_{EV,ik} = 0 \quad \forall i, k \notin \mathcal{T}_i \tag{7.59}$$

where $\mathcal{T}_i$ denotes the set of all time-steps for which vehicle i is plugged in. In this case $\mathcal{T}_i$ is determined fully when EVs are at home, but one could consider other configurations as well.

Fig. 7.10 compares the demand profiles in the case with and without charging availability constraints. The differences are rather modest, although one notices, as expected, that during the day time the EV load is somewhat smaller in the case with the availability constraints. This is due to the fact that during the day the number of EVs parked at home is smaller than during the night.

To analyze the effect on the network peak, we show the load duration curve of network load in Fig. 7.11. From this figure, too, we conclude that the differences in load profile are quite small. We note that the number of hours with a high load

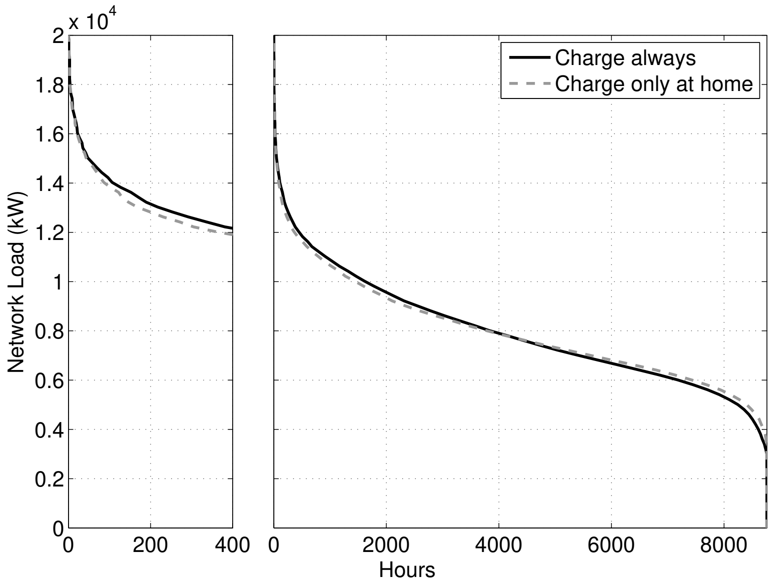


Figure 7.11 – Comparison of load duration curves between the case where EVs are always able to charge and the case where only charging at home is possible. The network load denotes combined household and EV demand.

has decreased slightly (visible in the left panel of the figure), so apparently the first effect discussed above is more prominent. The highest peak is equal in both cases though, because it occurs at a moment where all cars are actually plugged in. We thus conclude that the charging availability has little influence on the EV induced peak load. One reflective remark is considered appropriate here: in case EVs are also allowed to charge at work or parked near shopping centers, etc, the network load at the residential grid will obviously be lower. An analysis that takes such spatial effects into account is considered outside the scope of this thesis and forms an interesting venue for future research.

7.3 System level networks impacts of minimum cost charging

Chapter 4 evaluated the network impacts and financial consequences of EV charging by considering uncontrolled charging profiles as well as a controlled charging profile aimed to minimize the network load. We showed in chapter 6 and this chapter how minimizing the charge costs based on wholesale electricity prices can actually lead to even higher network peaks than the uncontrolled case. The question thus rises what the distribution network impacts and its financial consequences of these charge profiles are. Precisely this question was analyzed in [98]. Here we summarize a few key findings of this study; for more details we refer to the paper. The method used to convert network profiles to network impacts and cost figures was roughly the same as the one described in chapter 4.

In [98] three different EV scenarios have been analyzed: uncontrolled (identical to the one used in this thesis), minimizing network peak and energy losses (essentially the formulation in chapter 2, Eq. 2.20) and minimizing energy costs (7.58). A similar EV adoption curve as shown in Fig. 1.4 has been assumed, leading to roughly 50% EV penetration in 2030 which was the time horizon of this study.

Fig. 7.12 shows the NPV of all capital expenditures related to asset replacements and energy losses up to 2030. We observe that the higher peaks in the cost minimizing case indeed leads to significantly higher costs, in terms of higher energy losses and but most prominently in higher replacement costs. Interestingly, one also observes how energy losses are even higher in the minimum loss scenario that in the uncontrolled scenario. We explain this by recalling that the replacement of assets generally leads to lower losses. So the uncontrolled scenario may have lower losses, but at the expense of more costs for new assets.

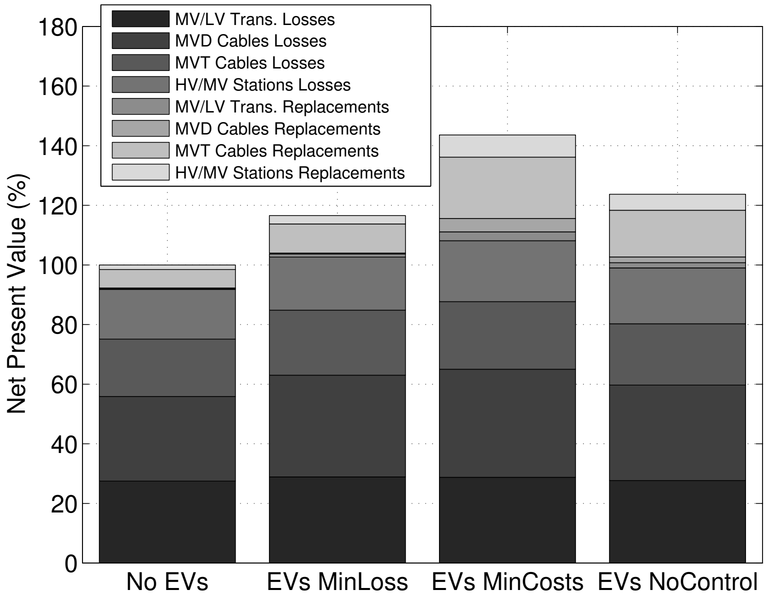
These figures are also interesting to interpret in the light of the results shown in Table 6.1. Here it was shown that for applying a congestion management mechanism to limit EV load to free asset capacity leads to negligible extra energy costs. Since *not* limiting the load indeed leads to much higher network costs (as shown clearly in Fig. 7.12), we conclude that it makes sense to consider a form of congestion management in the distribution grid. Although we already arrived at this conclusion in chapter 6, the figures presented here significantly strengthen this conclusion.

7.4 Other settings and applications for demand response

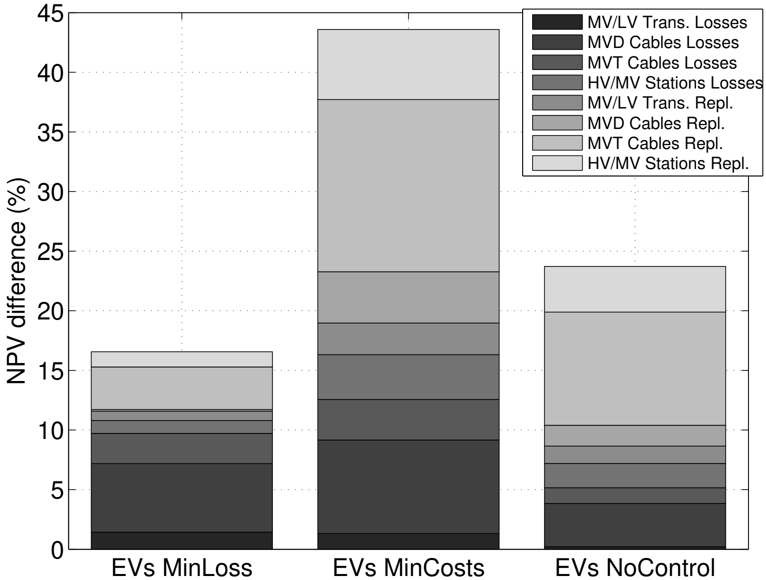
This thesis describes a range of asects of controlled EV charging. Other settings in which EV charging might offer great benefits are, however, also possible. Furthermore, although EVs have a number of characteristics that make them particularly suitable for demand reponse purposes, other forms of flexible electricity demand could start playing an important role, too.

One type of power systems that may particularly benefit from (EV) demand reponse are small isolated power systems on islands or remote communities [99]. By definition, they lack interconnection with neighbouring systems, so those benefits in terms of reliability or a smoother RES availability profile are not available. Furthermore, they often rely on expensive and polluting diesel or fuel oil generators for electricity supply. Marginal generation costs of such units can be in the order of 200-300 \$/MWh, which is a considerably larger than total levelized costs of wind and solar energy, see Fig. 1.2. However, installing large capacities of wind and solar power will quickly lead to curtailment[4], because there are no ways to export surpluses. Being able to adjust a portion of the demand to the wind power avaialibility thus has a great economic potential. In addition, it leads to much lower emissions

[4]Based on the exact total levelized costs of wind and diesel generation, say these are 100 and 200 \$/MWh, it would still be economically viable to install a capacity of wind power that heavily exceeds the average load, because even if 50% has to be curtailed, wind power still has a lower overall cost than diesel.



(a) Total costs components



(b) Cost differences components

Figure 7.12 – (a) NPV components of capital expenditures and energy losses for the HV/LV transformers, the MV distribution and transmission cables and the MV/LV transformers in the various cases. The values are normalized with respect to the NPV in the case without EVs. (b) Difference in NPV between EV scenarios and the case without EVs.

of CO_2 and other pollutants. Appendix A, based on the work described in [100], explores the potential of controlled EV charging in such a system in more detail. Important findings are that controlled EV charging indeed can replace a lot of diesel generation by wind and solar power, leading to lower generation costs and lower CO_2 emissions. Compared to diesel powered vehicle use and electricity generation, CO_2 reductions up to 85% are possible.

The demand response potential of EVs is largely due to the flexibility in the charging process, or, in other words, to shift its electricity demand in time. Many other types of electric loads have this ability, too. One that has received a lot of attention in the context of demand response and/or direct load control - long before EVs were even in the picture, see [101] - is the control of climate systems for heating and cooling of buildings. For such systems, too, optimization problems may be formulated based on economic objectives under the constraints of certain temperature bounds and the dynamics of the system under consideration. Whereas EVs have electrochemical storage in their batteries, thermal storage is their equivalent in climate control of buildings. The level of flexibility (how much and for how long one is able to shift the electricity demand) depends on physical parameters such as the heat capacity of the object and the heat transfer with the environment. The level of flexibility of, say, one single refrigerator is modest. One cannot pre-cool a refrigator to very low temperatures and then postpone the next cooling cycle by a few days. For larger systems with more thermal mass, such as cold storage warehouses or office buildings, the level of flexibility may be larger. Appendix E, based on the work described in [102], explores such a setting in more detail: a cold storage warehouse in combination with solar PV generation. Some of the main findings of this work are that the optimal cooling trajectories, the economic value of intelligent cooling and the maximum network flows all depend strongly on the electricity tariff structure. This, once again, demonstrates how the physical demand response potential is heaviliy interlinked with the economic environment it is embedded in.

7.5 Conclusions

This chapter explored a number of refinements to the analyses on EV charging from previous chapters. We considered differences in managing a fleet of EVs from a social planners point of view and decentralized price-based charging by cost-minimizing EV aggregators. It was found that, as economic intuition suggests, if the number of aggregators is small they can benefit from influencing market prices at the expense of higher generation costs. The differences with the socially optimum profile are modest, however, and quickly vanish when the number of aggregators grows. In a sensitivity analysis on inter-temporal generation constraints we compared a unit commitment formulation including EV scheduling with an approach that ignores all individual generator characteristics and minimized EV charging based on a linearized marginal cost curve. The results were found to be rather similar between both cases, which strengthens the confidence that EV aggregators minimizing their charging costs facilitate the integration of variable RES sources. The optimization horizon did not prove to be very critical, which gives some confidence that e.g. forecasting errors of wind production will not significantly hamper the potential of EV flexibility. Availability of EVs for charging had an equally limited effect on the EV profiles. Furthermore, a large-scale grid analysis similar to chapter 4, but this time focussing on the network peaks induced by cost-minimizing EVs reacting to wind power based wholesale prices, showed that these peaks indeed lead to substantial grid costs. Together with the finding of chapter 6 that limiting EV load to grid capacity leads to negligible extra energy costs, this essentially completes the argument for applying a form of congestion management in distribution grids.

Chapter 8

Conclusions and recommendations

This final chapter concludes the work described in this thesis by summing up its main results and insights. In section 8.1 we formulate a coherent answer to our main research question posed in chapter 1 and treat its underlying sub-questions associated with chapters 4, 5 and 6 in more detail. Furthermore, in section 8.2 we sketch the contours of a possible new paradigm for clean and intelligent power systems. We end this chapter with recommendations for future research and some considerations relevant for policy makers.

We start by listing the **contributions of this thesis to the state-of-the-art** in the scientific fields around the role of EVs in smart grids.

- A **large-scale analysis of distribution grid impacts of EVs and its financial consequences** for DSOs has been presented in [69] and chapter 4 of this thesis. Results show that when controlling the charging process the replacement costs are reduced most markedly, costs for energy losses are much closer between controlled and uncontrolled scenarios and an overall cost reduction in the order of 20% can be realized, the largest part of which to be found at the level of medium voltage cables.

- An analysis of the **combined potential of controlled EV charging and cross-border transmission capacity for integration of variable RES** has been presented in [76] and chapter 5 of this thesis. The main finding is that these technologies, that are often seen as substitutes, can complement each other in high RES scenarios.

- Possible **congestion management** mechanisms **to efficiently allign** the potential of EVs for **RES integration *and* the distribution networks** have been proposed and analyzed in [89] and chapter 6 of this thesis. Results indicate that applying an optimal congestion management scheme is economically efficient, but in the design a trade-off exists between simplicity and efficiency that needs to be considered more closely.

- Various **sensitivity analyses adding to the robustness of the conclusions** were presented in chapter 7. Particular findings are that decentralized price based charging only converges to socially optimal EV profiles for a large number of aggregators and the optimal EV charge profiles depend only slightly on 1) inter-temporal generator constraints, 2) an optimization horizon beyond two days and 3) the availability for charging during day-time. Furthermore, the large-scale distribution grid impacts of EVs reacting in a correlated way to wholesale electricity prices are costly even compared to uncontrolled charging, which strenghtens the case for congestion management.

8.1 Conclusions and answers to research questions

The central question of this thesis reads:

How can the flexibility of EV charging best be utilized in multi-actor power systems with high shares of renewable energy sources?

The two important perspectives from which controlled EV charging can add significant value are its ability to be shifted in time according to fluctuating RES output on the one hand, and to avoid peaks in network demand to defer or postpone network investments on the other hand. With flat network tariffs and wholesale prices that will be influenced strongly by fluctuating RES output, price responsive EV demand can lead to even higher demand peaks than uncontrolled EV charging. The required network reinforcements are costly and unnecessary because limiting the load to free network capacity through an efficient congestion management mechanism has negligible additional energy costs. There are various congestion mechanisms possible to allign the cost minimizing EVs with network constraints, either based on shadow prices associated with the network constraints or an ex-ante allocation of free network capacity, but in both approaches there exists a trade-off between simplicity and economic efficiency. All schemes, however, seem to have in common that the function of the DSO is extended beyond its current role.

Description of the role of electric vehicles in multi-actor power systems
The large-scale introduction of EVs and the continuing growth of variable RES poses a number of threats and opportunities to power systems. In liberalized power systems, different actors have different objectives that translate into different strategies with respect to these technologies. Distribution network operators generally have incentives, through some form of regulation, to minimize costs related to asset replacements and energy losses. Retailers and/or aggregators representing consumers have the incentive to minimize charging costs based on electricity prices. In the absence of market power, such objectives also lead to a minimization of variable electricity generation costs.

The flexibility of EV charging can be understood mostly by comparing the typical daily battery discharge of approximately 6 kWh with a typical battery size of 24 kWh. This gives EV owners the option to postpone the charging process by a few days. With the help of a linear equation that relates the battery energy content to charging power and discharges due to driving, the problem of finding an EV charging schedule that maximizes some objective can be described as a mathematical optimization problem. The objective function of this problem depends on the perspective of the relevant actor. An EV aggregator minimizes charge costs based on wholesale electricity prices and takes into account that the extra EV demand influences wholesale prices as well. A DSO minimizes peaks in network load, which results in minimizing the square of network load plus EV demand. EV charging can thus be scheduled intelligently to maximize the value of its flexibility.

Sub-question 1: How can the controlled charging of EVs reduce their impacts on the distribution grid? Large scale adoption of EVs leads to a substantial increase in the demand of electricity, which, if it coincides with non EV related demand, causes high peaks in network demand. If EVs charge solely at home, starting immediately after arrival at home, the resulting uncontrolled charging profile leads to a marked increase of the evening peak. In a controlled charging scenario, EV demand is transferred largely to the night hours resulting in a much flatter load profile and almost completely avoiding an increase in the evening peak. From the point of view of a DSO, the financial benefits of controlled EV charging are due to postponing and/or deferring grid asset replacements and lowering costs for energy losses. The difference in the net present value of investments and energy losses between the uncontrolled and the controlled charging scenarios is in the order of 20%. The biggest savings are to be expected on the level of MV-cables. We conclude that there is a strong financial incentive for controlled EV charging with the objective to defer network investments and lower energy losses.

Sub-question 2: How can controlled EV charging reduce generation costs in power systems with a high share of renewable energy sources? The variable nature of renewable energy sources causes large fluctuations in the residual load that is served by conventional, dispatchable generators. Flexible EV demand can be explicitly included in the optimal scheduling of generation units, leading to a flatter output profile of the dispatchable units. Compared to an uncontrolled EV demand profile, controlled EV charging leads to a reduction in variable generation costs by shifting load from expensive peak units to more efficient base-load units and by reducing the number of start-ups.

Another way to deal with the intermittency of renewables is the exchange of power between interconnected nodes, because averaging the RES output over a larger area leads to a flatter RES production profile. In a setup with two interconnected power systems with different variable RES profiles, EV demand response and interconnection between the nodes proved to be substitute technologies that independently lead to a reduction in generation costs for moderate RES penetration scenarios. For high RES penetration, however, it was found that EV demand response and cross-border transmission capacity actually strengthen each other, because transmission capacity is needed to transport power to locations where there is sufficiently much flexible demand to absorb it. It is thus concluded that in future high RES scenarios there are financial benefits for *both* EV responsive demand and increased interconnection capacity.

Sub-question 3: How can the costs of EV charging be minimized within distribution grid constraints? Because RES lead to a reduced correlation between electricity price and network load, low electricity prices can occur simultaneously with high network demand. As a result, flexible EV demand reacting to wholesale electricity prices can create large peaks in network demand. Because these peaks only occur during a few hours per year, limiting the flexible EV load to the available network capacity increases energy costs only marginally. Hence, without an additional mechanism that gives an incentive to take network load into account, the EV peaks may cause unnecessary and costly reinforcements of distribution network components.

A number of congestion management mechanisms that aim to avoid distribution grid overloading have been analyzed by modeling an EV fleet reacting to electricity wholesale prices in a system with a high RES penetration. The first mechanism is a unilaterally determined dynamic grid tariff based on a shadow price associated with the limited line capacity. Although an optimal tariff indeed limits EV load to the free line capacity, it is, however, difficult for a DSO to determine because it requires full knowledge of all EV preferences and wholesale price forecasts. Furthermore, the bi-level programming problem that should be solved to determine this optimal dynamic grid tariff is hard even in the case of perfect knowledge and could be infeasible to determine in practice in the presence of uncertainties.

A distributed approach where DSO and EV aggregators iteratively exchange updated grid tariffs and EV demand profiles also converges to the optimal dynamic grid tariff. The main advantage of this scheme is that it requires a DSO only to forecast (non EV related) network load, whereas EV aggregators predict EV preferences and wholesale prices. Because these types of information lie much closer to the core tasks of the two respective actors, it is a more natural setup than the unilaterally determined grid tariff. The main disadvantage is that this scheme is of higher complexity and requires more IT infrastructure since information has to flow iteratively between DSO and EV aggregator.

A third possible mechanism, advance capacity allocation, is not price based but capacity based. Here the main challenge lies in the allocation of the capacity in the case where multiple EV aggregators represent EVs on the same distribution line. An auction of capacity, where EV aggregators announce time-dependent demand curves for distribution grid capacity, is complicated by the inter-temporal constraints related with EV charging. These constraints make the demand curves in future time-steps dependent on the amount of allocated capacity in previous time-steps.

Simple proxies for the optimal dynamic grid tariff have also been analyzed and were found neither to solve the congestion issues, nor to be economically efficient because they unnecessarily distort the economic signal of wholesale electricity prices. Their use is therefore not recommended.

We conclude that there exists a trade-off between the simplicity and the efficiency of possible congestion management mechanisms for responsive demand in the distribution grid. Issues related to uncertainty and requirements on IT infrastructure should therefore be taken into account when further investigating these mechanisms.

A refined view on EV charging EV demand can either be scheduled centrally by a social planner aiming to minimize total generation costs, or in a decentralized approach where EV aggregators aim to minimize the charging costs. In the extreme case of one single aggregator who schedules all EV demand and thereby minimizes his charge costs, an EV demand profile that is different from the social planner's optimum results. This can be ascribed to the fact that a single aggregator can schedule a small portion of demand against higher prices and then benefits from lower prices for the much larger remaining part of the demand. Multiple aggregators that take each other's actions into account, do lead to an aggregated EV demand profile that converges to the socially optimal profile. A well functioning market that includes price-elastic electricity demand therefore requires a number of competing aggregators.

From a sensitivity analysis that explores the effects of inter-temporal generation unit constraints, the length of the forecast horizon and the availability of EVs for charging, it was concluded that these factors have in general a rather modest effect on the EV charging profile. These results thus strengthen the confidence in the conclusions described above and show that also under very different assumptions there can still be large benefits in controlled EV charging with respect to grids and/or generation costs. Furthermore, we showed that the impacts of EV demand responding to wholesale prices indeed incurs substantial costs related to distribution grid upgrades.

8.2 Contours of a new paradigm for a clean and intelligent power system.

In this thesis we explored how flexible EV demand can provide value with respect to different functions and for different actors in a power system. In principle, most of our analysis of the potential value of flexibility was done from the perspective of the current institutional design. One could question whether these current settings allow this flexibility to be exploited optimally. Whereas the reforms towards restructured power systems in the 80s and 90s were largely driven by 'the need for growth in productivity and efficiency' [17] , the main objective of today must be to develop a set of rules in which the use of clean electric energy, with its typical and irregular characteristics, can be used optimally.

We have shown that the main value of flexible demand lies in its ability to adjust according to the fluctuating and uncertain RES output. When recalling the definition of flexibility as *the extent to which a power system can modify electricity production or consumption in response to variability, expected or otherwise* [12], we note that there are already many possibilities in today's power system for flexibility: bilateral contracts, day ahead markets, intraday trading, balancing markets, interruptible load contracts, etc. But as flexibility will become more and more crucial, the notion of some type of market for 'flexibility products or services', however those may exactly be defined, could become necessary, like also briefly discussed in

[16], chapter 14. Here it was also noted that the development of a market for such products will attract the necessary investments in flexibility enabling technologies.

One natural suggestion in this line could be something like a 'flexible demand quotum', defined as a contract for a certain amount of energy in a certain time frame, regardless of the exact timing. For example, if a consumer parks his electric vehicle at 6PM and leaves the next day at 8AM and he needs 6kWh to recharge, he could buy such a flexible demand quotum: 6kWh (6PM-8AM). Quota spanning a longer time frame could be offered at a lower price. Similarly, for storage one could think of a 'flexible supply quotum': a storage facility has an amount of energy to offer, but it does not care when exactly it will produce. When being able to offer such types of products, the burden of forecasting and planning is transferred from the parties offering flexibility to the ones needing it. The existence of a market where flexibility services are rewarded appropriately could also accelerate the emergence of aggregators - the intermediate parties intelligently operating flexible demand resources of consumers.

However, one of the main points of this thesis was that demand flexibility has a value both with respect to variable RES generation *and* the distribution networks. The question thus remains what the future role of the DSOs should look like. Should they, for example, also be allowed to purchase flexibility products like the ones described above? Or alternatively, are other congestion management mechanisms like the ones discussed in chapter 6 of this thesis adequate? We showed in chapters 6 and 7 how price responsive EV demand under the current rules and tariffs can lead to unnecessary and costly investments in distribution grid upgrades. All of the possible congestion management mechanisms to remedy this issue have in common that there is role for DSOs that extends beyond their current mandate. The DSO as a 'passive' copper building entity seems not to fit the image of an efficiently operating power system where all functions in the value chain of electricity supply are aligned. With the right governance structure, unnecessary investments can be avoided while still facilitating the optimal use of clean generation technologies.

When DSOs will indeed will be more actively managing the distribution networks, their role becomes more similar to that of today's TSOs, although there are fundamental differences too. Congestion management on the distribution networks, for example, involves not a few large companies like the generators/retailers for the transmission system. Instead, many small players, possibly represented by a much smaller number of aggregators, on thousands of different network would engage in economic activities for electrical energy and/or network capacity. Transaction costs will thus matter. Furthermore, small consumers can not be assumed to be always pursuing minimization of costs, which could result in larger fundamental uncertainties regarding their load profiles and response to economic signals. Another complicating factor, as discussed in chapter 6 are the inter-temporal constraints associated with demand response and/or storage, which makes it much harder to quantify energy and network capacity needs for a certain period ahead of time. Uncertainties on local production and demand complicate this even further. In summary, if DSOs will become a sort of mini TSOs, they will do so in a much more complex playing field.

One could even speculate that the complexity of facilitating demand response with competing aggregators raises the question if the benefits outweigh the transactions costs that are inevitably part of such a complex system. If, for example, a DSO simply assigns one single EV aggregator (or acts as one itself) for a part of its service area, the complexity and hence transaction costs would be reduced strongly. The disadvantage is that this aggregator thus has a natural monopoly position, and will need to be regulated. This will be a departure from the very unbundling philosophy, since now commercial activities will fall in the regulated network domain. In a way, these reflections touch upon the 'limits of the unbundling', because the fact that centralized coordination can be so much easier and more efficient should be weighed against the invisible hand of the market.

A more pragmatic approach would be to allow the EVs (or other flexible demand) to induce network loads that are higher than the safe N-1 capacity. In case of the rare simultaneous event of a line fault together with a high EV load, the EVs can simply be curtailed. This does require an infrastructure to physically curtail the EV load, but this will likely be much less costly than an IT infrastructure enabling 'dynamic' congestion management plus its transactions costs. Generalizing this notion, one could question whether the N-1 criterion makes sense in the clean and intelligent power systems we should be moving towards.

8.3 Recommendations

8.3.1 Future work

A number of recommendations for future research can be extracted from the work described in this thesis. The two fundamental characteristics of RES making them more difficult to integrate in the power system are variability and unpredictability. For both these problems, flexible electricity demand might offer solutions to some extent. While the former has been treated extensively in this thesis, the issue of uncertainty and the potential of EVs to deal with it have not been treated. This issue has received quite some attention in the literature (see also chapter 3), but many open questions remain. The deterministic optimization approach that was used for the work described in this thesis should then be abandoned and stochastic techniques should be used instead. Essential for these models are realistic forecasts - of RES production and demand - including probability distributions of the forecast errors. Ensemble weather forecasts could provide the basis for these probabilistic RES output predictions. The resulting problems of decision making under uncertainty require more advanced optimization and planning techniques and will computationally be more demanding too.

Closely related to the above is the issue of EV participation in balancing markets. This topic, too, has already received quite some attention in the literature, but important questions remain. For example, balancing and/or intraday markets are often organized differently in different countries or power systems. An exploration of the potential of flexible demand in different contexts is considered a valuable addition to existing literature. Such analyses can also contribute to the broader research question how (balancing) markets with extremely large penetrations of RES can best be organized in the first place. An issue that follows directly from the above considerations is how distribution grid impacts of EVs participating in balancing markets would turn out. One could speculate that without proper network related financial incentives, the grid impacts of responsive (EV) demand reacting on balancing signals could prove to be even worse compared to the case described in this thesis because balancing markets have more volatile prices than day-ahead markets.

Another topic that is worth investigating in more detail is how *investment* in generation and/or transmission capacity is influenced by the large potential of flexible EV demand. In chapter 5 we only considered the effect of transmission capacity and EV management on *variable* generation costs. The question how optimal portfolios of RES, conventional generation and transmission capacity look in relation with demand response is therefore considered worth investigating in more detail. Following this issue are related questions such as what policy instruments give proper incentives to arrive at the right technology mix when a significant volume of demand response is present.

Also related to the topic of investment is an analysis of efficient planning and cost recovery in distribution grids. We analyzed in chapter 6 how congestion management in a given distribution grid could be designed, but we left untouched the question of investment and cost recovery in new grids. These topics are also tightly related through the collection of congestion rents by the DSO. Care should be taken that DSO do not have incentives to underbuild capacity. It is not unthinkable that the introduction of large amounts of price responsive demand changes the landscape in electricity distribution so profoundly that new regulation schemes should be investigated. One could, for example, think of incentives for price responsive demand to reveal their long-term demand curves for network capacity. We noted in chapter 6 that it is more logical that the responsibility for short-term forecasting of EV demand and electricity prices should lie with market parties instead of DSO's, but the same could be true for long-term demand for network capacity. More research in this area is therefore recommended.

Throughout this thesis, we explored the potential of EV demand control under the assumption of 'rational' EV owners. The word rational is enclosed by quotes since equating 'cost minimizing' and 'rational' would not do justice to many factors that drive people's behavior. For instance, one could hardly call it irrational to always want to have a full EV battery in case an unexpected event requires the immediate use of the vehicle. Instead of 'cost minimizing', one could thus better use the term 'utility maximizing', but then the questions arises: 'what is the utility function?'. How much, to continue the example, are people willing to pay to always have a full battery? Determination of a 'utility function' is difficult, and the answer should not be looked for in the realm of exact sciences, but rather in social, behavioral and psychological fields. In this light it is also interesting to note that there are indications, in the context of an energy management system experiment, that people are equally or sometimes even more motivated by environmental than financial incentives [103]. Alternatively, instead of focusing on 'utility', another promising approach could be to consider 'regret'. Empirical evidence in a travel-mode choice experiment shows that regret-minimization is sometimes a better way of representing people's choices than utility-maximization [104]. Similar experiments in relation to demand response could shed more light on the question how to unlock the demand response potential, the benefits of which have been explored in this thesis.

8.3.2 Considerations for policy makers

In this thesis EVs were considered not simply as electric loads, but rather, by tapping into their inherent flexibility, as building blocks of intelligent energy systems. One advice to policy makers as therefore to do the same and formulate new EV policies from the broader perspective of intelligent power systems. Especially in the light of the transition towards a renewable energy based power sector it makes sense to coordinate RES and EV policies - not only because of natural combination of flexible demand and variable supply, but also since EVs powered by RES have the potential to substantially reduce emissions in the transport sector. With regard to the networks, we showed that congestion management of price-responsive EV charging has a very low extra energy cost but saves considerably in terms of additional network investments. When the EV load reaches considerable magnitude, the application of some form of congestion management and its required changes in the institutional and regulatory structure are therefore recommended.

Although we have only briefly touched upon the issue of CO_2 emissions and their relation with EV charging in this thesis, some concluding remarks and recommendations are justified. In chapter 5 and appendix D we showed that as long as coal (and/or lignite) generation have the lowest marginal cost of generating electricity, any form of price based control of EV charging will lead to an increase in CO_2 emissions, which will strongly affect the CO_2 reduction potential of a large-scale switch to electric mobility. Furthermore, it will weaken the business case for cleaner and more flexible gas generators and, instead, increase the number of hours coal plants are running. We conclude that the current CO_2 policy (or more specifically: ETS and its current price levels) not only fails in attracting enough investment in clean energy technologies, it also gives incentives to operate a given portfolio in the most polluting way. We therefore recommend a re-thinking of current CO_2 policies in the light of the intelligent power systems of the future.

A recommendation that follows from the analysis in chapter 7 of this thesis, is that governments should warrant that no market power on the demand side of electricity is exercised, as we showed that this leads to economic inefficiencies. Current regulation focuses more on preventing market power on the supply side of the electricity market, but as large volumes of price responsive EV demand may one day become reality, there might emerge a need to guarantee a well functioning market for the demand side as well. We demonstrated how in systems with only a small number of EV aggregators the combined EV demand quickly approaches the socially optimal demand profile, so keeping this market reasonably liquid seems desirable.

Perhaps the most important advice, and also the most firmly funded by the work in this thesis, is to reconsider the rules and roles of today's power sector in the light of clean an intelligent power system. We sketched above some of the contours of such a system and we advice policy makers to start looking in the right direction, because the long lifetime of infrastructure assets requires todays policies to be aimed at tomorrows objectives.

Final thoughts

Scientific progress, by increasing labor productivity and technological efficiency, has led to an enormous growth in prosperity for a large part of the world. Among the darker sides of this picture are a dangerously close approach to ecological limits and a deeply unequal distribution of wealth. New scientific developments and technological breakthroughs, not in the least those in the energy domain, are now creating renewed opportunities for a better world. Focusing on the ecological dimension, it seems that technology is no longer the limiting factor to a more sustainable world. Renewable energy sources are becoming ever cheaper, their growth in many countries is spectacular and new ways of operating highly renewable systems are being studied by many enthusiastic scholars and professionals. The crucial economical and institutional aspects, too, are subject of study by researchers and policy advisors worldwide and contours of new governance structures are beginning to appear. Although much work still needs to done, this thesis has hopefully contributed a minuscule piece to coming one step closer to a sustainable energy system.

Appendix A: The potential of EVs in an isolated power system

This appendix is based on the work described in [100].

Introduction

In this appendix we briefly discuss the role of EVs on an island with a high RES penetration. The system is modeled using data from the Azores island Flores, which has approximately 4000 inhabitants, a peak load of roughly 2 MW and electricity generation by wind, hydro and, mostly, diesel power.

The analysis presented here are treated in more detail in [99], chapter 11. The main new elements compared with the rest of this thesis are:

- EVs were assumed to have V2G capabilities, i.e. they can discharge power to the grid.
- A deterministic dynamic programming algorithm instead of a linear or quadratic programming was used to calculate the optimal EV dispatch.
- A small isolated power system with a very high penetration of renewables was studied. The characteristics of this power system are such that there is a high curtailment of RES, and, secondly, expensive diesel generators are used for periods with too little RES output.
- Reduction of CO_2 emissions was analyzed.
- The effect of controlled EVs on the optimal generation mix was investigated.

Residual demand curves

The residual demand curves depicted in Figs. 1(a) and 1(b) show that there are many hours with a surplus of renewable generation. The EVs, when charging is

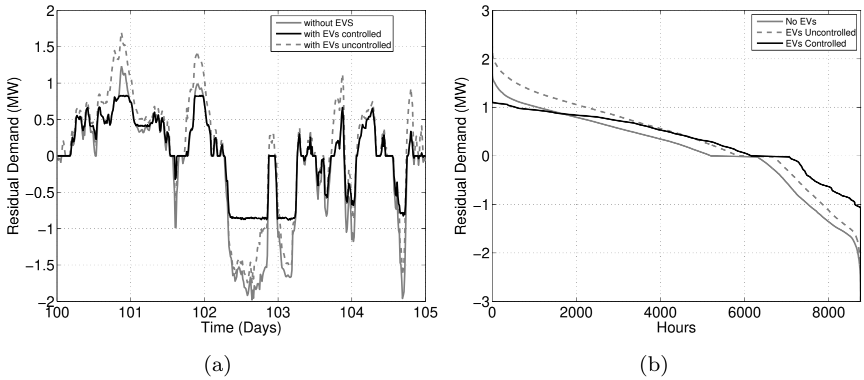


Figure A.1 – Residual demand for the moderate wind and solar scenario and 1000 EVs in a five day spring period (a) and the load duration curves (b).

Table A.1 – Total (electricity generation + vehicle emissions) yearly CO_2 emissions in kton for different scenarios.

Electricity Scenario	Vehicle Scenario				
	All Diesel ICE	50%EVs Uncont.	50%EVs Cont.	100%EVs Uncont.	100%EVs Cont.
Current generation mix	8.38	8.08	8.06	7.80	7.76
Moderate Wind and Solar	6.18	5.37	4.65	4.26	3.05
Aggressive Wind and Solar	5.52	4.42	3.29	3.13	1.29

controlled, manage to absorb a significant portion of this surplus. Nonetheless, a significant share of renewable generation has to be spilled. Fig. A.2 shows the different generation technologies for the same five day spring period. These graphs readily show how the controlled EV charging leads to an increase in demand in times of a surplus wind and solar generation. Also, since V2G capabilities were assumed here, the amount of diesel generation is reduced, even compared to the case without EVs.

Effects on emissions

From the obtained time series of dispatched diesel generation, the CO_2 emissions can be calculated in a straightforward manner, assuming that the diesel generator emits 0.7 ton/MWh [105]. We compare the total emissions of the island under different electricity generation and vehicle scenarios. Currently the fleet of roughly 2000 passenger cars is mostly powered by an internal combustion engine (ICE) fueled with diesel with a typical emission of 150 g/km [106]. Table A.1 gives an overview of the total emissions in the various scenarios.

The most important conclusion from this table is the large emission reduction potential that EVs offer in combination with renewable generation. In the most aggressive scenario, the total reduction of CO_2 emission is more than 85% compared to the current situation. In this scenario, the *value* of controlled charging is also the

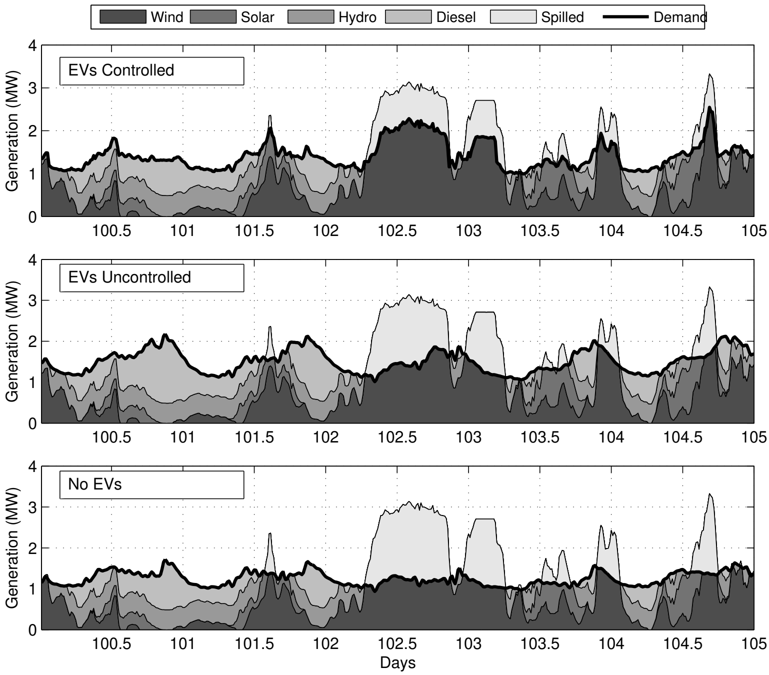
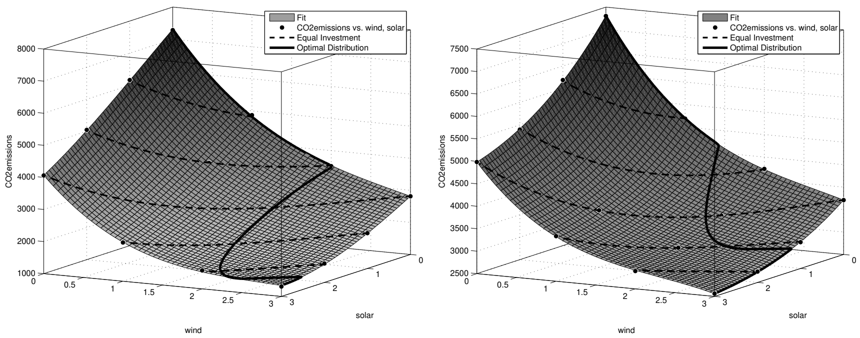


Figure A.2 – Use of different generation types for a period in spring with 1000 EVs in different scenarios for the case with maximum wind and solar distribution.



(a) 1000 EVs Controlled

(b) 1000 EVs Uncontrolled

Figure A.3 – CO_2 emissions as a function of installed wind and solar capacity in both the controlled (a) and uncontrolled scenario (b). Also shown are the line of the optimal mix and lines of equal investment. The units of wind and solar capacity are dimensionless and are such that the maximum of 3 correspond to 4.1 MW for wind and 4.0 MW for solar.

most prominent: a reduction of more than 60% (from 3.13 kton to 1.29 kton), only due to shifting the energy needs of the vehicles. This confirms the intuition that the value of 'smarts' increases when more RES in installed. The table shows also that with the current generation mix that is dominated by diesel, replacing ICE diesel cars with EVs leads to only modest emission reductions.

Optimal wind and solar mix

If one is interested in reducing CO_2 emissions, it is instructive to compare the cost effectiveness of investments in wind and solar generation with respect to the emissions of CO_2 . By varying the amount of installed wind and solar and running the model for the whole year for each combination, the emissions as a function of installed wind and solar have been determined. To take into account that wind has lower total levelized costs than solar [3], the extra capacity of solar has been scaled according to the ratio of levelized costs, so that one unit of capacity of wind has the same costs as one unit of capacity in solar. In terms of installed capacity, the maximum value of 3 corresponds to roughly 4 MW for both technologies. Figs. 3(a) and 3(b) show the resulting CO_2 emission as a function of installed wind and solar capacity for the case with 1000 EVs (controlled and uncontrolled). Since the capacity scale was choses such that one unit of wind has the same costs as one unit of solar, the lines given by wind + solar = Const. denote the lines of a certain investment. The values of wind and solar where these lines are minimal then correspond to the optimal distribution of a given amount of investment in new capacity. So in both the uncontrolled and the controlled EV charging scenario, it is better to invest in more wind capacity first. At some point, however, building more wind leads to much more spilled generation and it is better to diversify the generation mix by adding some solar, despite the fact that this is roughly two times more expensive. An interesting observation is that the optimal mix depends on whether or not there is controlled charging of EVs

Table A.2 – Percentage of spilled renewable generation (wind + solar) for different scenarios. Recall that the amounts of installed renewables are larger in the case with 100% EVs by approximately 20%.

Electricity Scenario	Vehicle Scenario				
	No EVs	50%EVs Uncont.	50%EVs Cont.	100%EVs Uncont.	100%EVs Cont.
Current generation mix	0	0	0	0	0
Moderate Wind and Solar	28 %	21%	10%	23%	8%
Aggressive Wind and Solar	49 %	42%	30%	45%	29%

in place. In the controlled EV scenario, the EVs are able to avoid spilling energy much longer, so here it is beneficial to build more of the cheaper wind capacity. But even in this case, at some point it becomes more beneficial to invest in extra solar instead of building more wind. To understand the results on the cost effectiveness of new wind and solar generation, it is useful to invoke the amount of curtailed renewable energy (hydro has not been counted as such). Table A.2 lists the amount of spilled renewables in the different considered scenarios. It is important to notice that in the current generation mix there is never any spilling of wind or solar, but this is partly a result of the fact that we did not include start-up or ramping costs of diesel generators. In practice, some diesel generators will probably be kept running while wind is spilled, mainly for reliability reasons. The table also shows that in the moderate wind and solar scenario, the EVs are very effective to avoid curtailment of wind or solar. At some point though, there is simply to much extra energy to absorb and the amount of spilled energy starts to increase dramatically. Considering cost effectiveness, it is good to compare Table A.2 with the levelized cost of wind, solar and diesel. As stated before, with current diesel prices, the marginal costs of diesel generators are in the order of 250-300 \$/MWh. In [3], levelized cost of wind and solar are roughly 100 \$/MWh and 200 \$/MWh, respectively. This means that if 60% of all wind is spilled, it is still cheaper than diesel generation. For solar this is the case if 20% is spilled. These numbers strongly suggest that it does not only make sense to invest in wind and solar from an environmental point of view, but also from an economical.

Appendix B: EV impacts in residential low voltage grids

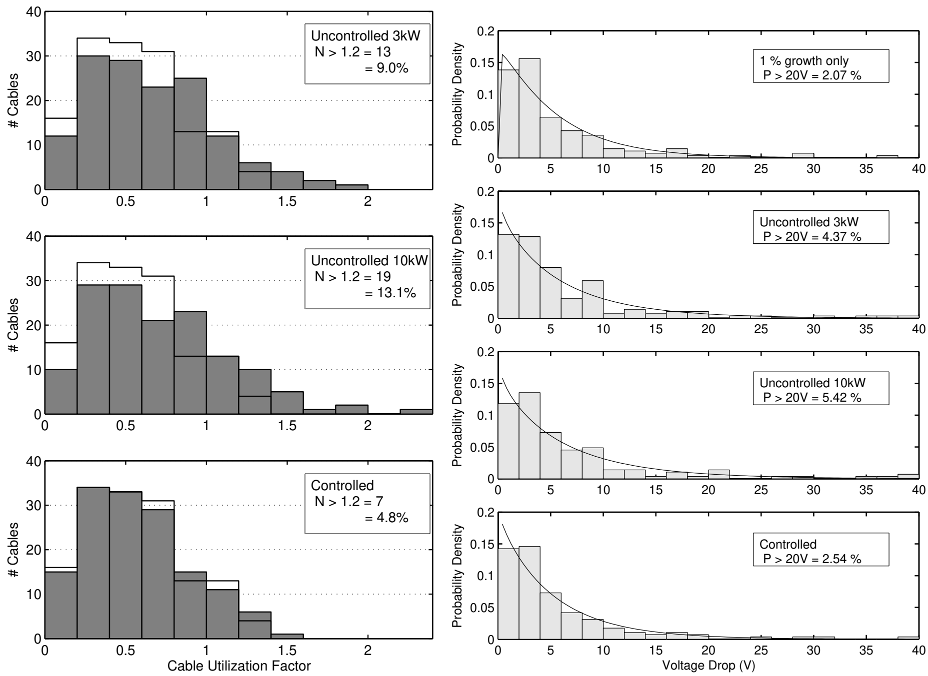
This appendix is based on the work described in [72]

In chapter 4 the effect of EV charging on distribution grid assets ranging from the MV/LV transformers to HV/MV substations was analyzed. The lowest level of distribution grid asset, the LV feeder cables, were not included in this analysis. This appendix presents some results of an analysis of EV impacts on LV feeder cables. The dataset used was substantially smaller (145 LV cables) than the one used in chapter 4. This is explained by the fact that the load on LV feeders is not measured in normal operation, so only data that has been collected during specific measurements was available.

Fig. 1(a) shows the histograms of LV feeder cable loadings resulting from a 75% EV penetration in 2040. Compared to the loadings of the other assets, only a modest number of overloadings is observed. This can partly be explained by the fact that LV feeder cables are generally over-dimensioned in comparison with the MV/LV transformers.

Another issue that is relevant for LV feeder cables is the voltage drop along the cable. Fig. 1(b) shows the voltage drops between the MV/LV transformer and the end of the cable for different EV charging modes. Because of the small dataset, a Weibull distribution has been fit to the data in order to estimate the probability of a voltage drop larger than 20 V. We note that these probabilities are very small, although, as expected, the extra EV load in the uncontrolled charging scenarios increases the probabilities markedly.

In conclusion, we note that the LV cable overloadings or voltage problems are much less pronounced than the impacts on the higher network levels that were analyzed in chapter 4. One important assumption should be repeated here, though. When calculating the impacts on the LV cables, we also used the aggregate EV demand profiles shown in chapters 2 and chapter 4. In chapter 2 we also showed, however, that the use of the aggregate profiles was only accurate for a number of EVs exceeding approximately 50. A typical LV cable serves around 20-25 households, so actually the use of the aggregate profiles was not quite accurate for this network level. One could suggest to correct the peak load by a certain factor, or, even better, to perform a stochastic analysis that assesses the probability of overloadings. This is left as a recommendation for future research.



(a) Cable loading distribution (b) Voltage deviation distribution

Figure B.1 – Change in cable loadings (a) and voltage deviation (b) if 75% of all households owns an EV in different charging scenarios. The line graphs in (a) denote the 1% growth scenario without EVs. Figure (b) also shows estimated (line graphs) probability density functions based on a Weibull distribution

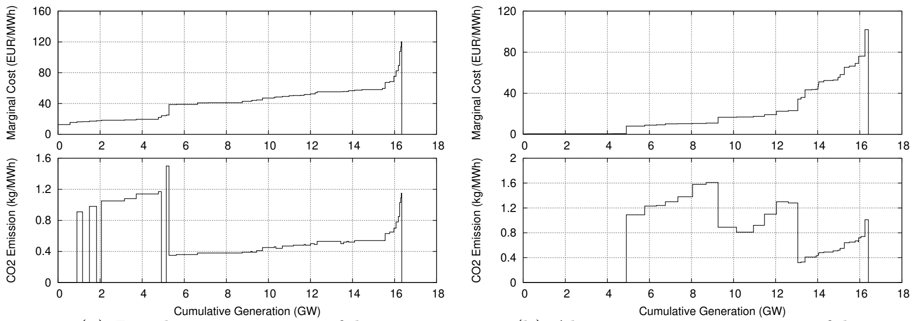
Appendix C: Carbon emmissions due to EV charging

This appendix is based on the work described in [107].

Introduction

CO_2 reduction is one of the important drivers for electric mobility. The exact CO_2 reduction of EVs is, however, determined completely by the electricity generation technologies employed to charge the EVs. When effectively powered by a coal plant, an EV has a similar emission per kilometer driven than a gasoline powered conventional vehicle. For example, assuming an EV efficiency 0.15-0.2 kWh/km [13] and a typical coal emission of 1000 g/kWh [108], one finds a CO_2 emission range of 150-200g/km. By contrast, the average CO_2 emissions of *newly sold* conventional gasoline vehicles in the EU in 2013 is around 130 g/km, whereas the average CO_2 emissions of the current passenger car fleet are around 180 g/km [109]. An EV powered by a coal plant hence has a considerably higher emission than a modern efficient gasoline vehicle.

The use of gas plants for EV charging reduces the emissions considerably by roughly 50%. When powered by RES, an EV drives virtually CO_2 free, except for emissions related to car manufacturing, road construction and other life-cycle effects. How charging EVs contributes to CO_2 emission at the system level depends on factors like the generation mix (how much coal, gas, wind energy etc is installed in a country) and the timing of EV charging. Furthermore, the order in which various power plants are dispatched (i.e. the merit order) depends on price of fossil fuels and non-fuel related variable costs like CO_2 pricing. In this appendix we analyse how EV emissions depend on these factors. In particular we study how emissions of EV charging depend on 1) the generation mix 2) the timing of charging 3) wind energy and 4) CO_2 price.



(a) Dutch generation portfolio (b) Alternative generation portfolio.

Figure C.1 – Merit order and marginal emission function of power plants for the Dutch generation portfolio (a) and the alternative generation portfolio based on the German fuel mix (b).

Research method

The analysis is done based on a simple model of the electricity system where it is assumed that power plants are dispachted according to increasing marginal costs of electricity production (i.e. the merit order). By combining the merit order of power plants with the system demand time series, the dispatch of power plants is found for each time-step. This model thus ignores start-up costs, minimum power output levels, ramping rates etc. Two different generation portfolios have been analysed. The first is the Dutch portfolio, with power plant characteristics originating from [23, 93, 97]. The second portfolio is inspired by German fuel mix statistics [110], which are characterized by a large share of coal and lignite (50%), nuclear (20%), gas (20%) and hydroelectricity and wind (10%). Taking into account typical plant sizes and efficiencies, we thus create a portfolio that is representative for the German portfolio; we will, however, refer to it as alternative portfolio. The total installed capacity still has the value of the Dutch total installed capacity used for the original Dutch portfolio, for reasons of a fair comparison between the two cases.

Caloric values of the different fuel types (e.g. as given in [111]), together with plant efficiencies allow us also to compute the instantaneous CO_2 emissions of electricity generation. We do not consider upstream emissions. Emissions of nuclear, hydro, waste incineration, biomass and wind have all been set to zero. It should be noted here that because nuclear plants have a must-run character, we have artificially put their marginal costs at zero, so they are first in the merit order. Fig. C.1 shows the supply function of the both portfolios, together with the CO_2 emissions of the plants ranked according to marginal costs.

To assess the impacts of EV charging, EV demand profiles are added to the system demand of electricity. We consider two stylized EV load profiles: one where EV charging is mostly done in the evening peak hours (referred to as peak charging) and one where the EV demand is shifted to the night hours (night charging). Furthermore, we assume a peak EV load of 1 GW, an EV driving efficiency of 5km/kWh

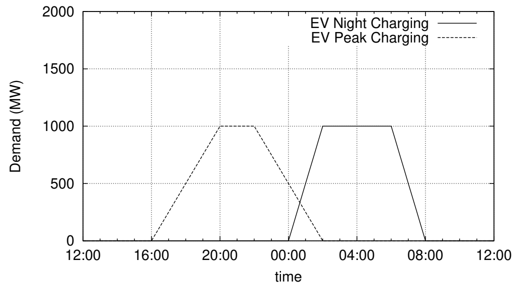


Figure C.2 – Extra system load caused by EV charging.

Table C.1 – Simulation results for different portfolios and different times of charging.

	Dutch portfolio		Alternative portfolio	
	Additional by EVs (kg/kWh)	Average (kg/kWh)	Additional by EVs (kg/kWh)	Average (kg/kWh)
No EVs	-	0.60	-	0.60
EV Night	0.45	0.59	1.25	0.61
EV Peak	0.53	0.59	1.05	0.61

and a total of one million EVs. The two EV charging profiles have been plotted in Fig. C.2. The yearly emissions caused by EV charging are found by the difference in total emissions in the case with EVs and the case without EVs.

Results

Emissions of EV charging for different portfolios

The emissions caused by EV charging in both portfolios are listed in Table C.1. We discuss the case with the Dutch portfolio first. For the average CO_2 emission of electricity production, we found a value of 0.60 ton/MWh, which is in close agreement with literature values of 0.55-0.60 ton/MWh [112]. We notice the difference in CO_2 emissions between night charging and peak charging due to the system load (including EV charging) at night being mostly around 9 GW, whereas peak loads range between 12 GW and 17 GW (summer and winter). Comparing this with the marginal emission curve from Fig. C.1, we conclude that for night charging the most efficient gas plants are the marginal plants and for peak charging the less efficient gas plants are dispatched. Worth noting is the fact that both at night and at system peak, EV charging emissions are still lower than the average CO_2 intensity of all electricity generation. This is due to the fact that the most polluting coal plants are included in the average CO_2 intensity, but do not contribute to the extra emissions caused by EV charging.

We observe remarkable differences in the alternative portfolio in comparison with the Dutch portfolio results. Most notable are the much higher emissions for both peak and night charging. This can not be readily understood if one takes into account that the average CO_2 emission of electricity production is about equal to

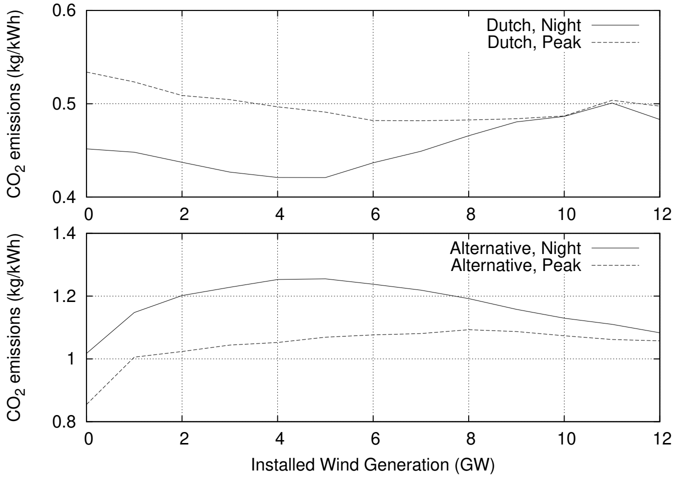


Figure C.3 – CO_2-emissions of EV charging as a function of installed wind power generation

the Dutch case. Invoking the marginal emission curve plotted in Fig. C.1 explains this result: the most polluting generation is found towards the end of the merit order. So, the extra emissions caused by EV charging are always higher than the average emission. The marginal emission curve also explains the fact that peak charging is in this case less polluting that night charging; a result that is opposite to the Dutch situation. Night charging is mostly done at a system load where either lignite or coal plants are the marginal plants, whereas peak charging takes place in the regime where gas plants are marginal. The fact that we find equal *average* CO_2 intensities of electricity generation for the Dutch and the alternative portfolio and completely different emissions caused by EV charging, unmistakenly points out that using average CO_2 intensities for calculating the environmental impacts of EVs is inaccurate.

The effect adding wind energy to the portfolio

When wind energy is added to the portfolio, emissions of EV charging will change due to the fact that wind has zero marginal cost and hence shifts all other generation to the right in the merit order. In the merit order dispatch model that is used in this analysis this is equivalent to subtracting wind power from demand. Fig. C.3 shows the effect of installing extra wind generation on the EV charging emissions on the Dutch and the alternative portfolio respectively. The results are again markedly different between the two different portfolios. In the Dutch case, initially wind power replaces the least efficient gas plants at the end of the merit order. At some point there is so much wind power that occasionally coal plants will be the marginal plants and the average EV charging emissions will start to rise again. In the alternative portfolio, initially the most polluting plants are pushed out of the merit order by wind power and we observe rising emissions. At some point nuclear plants will become the marginal plants and the EV charging emissions will decline

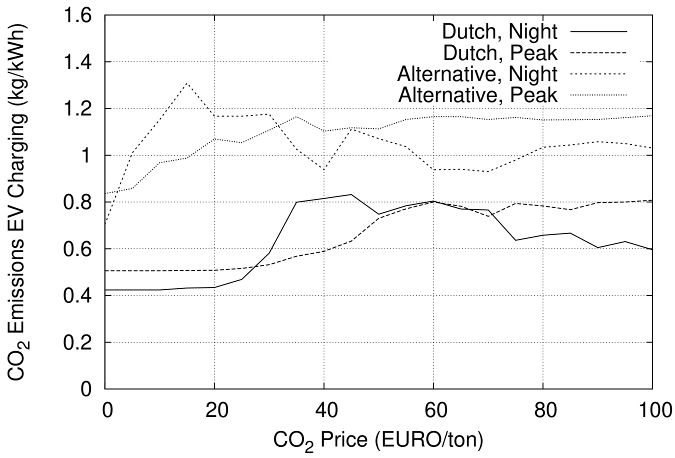


Figure C.4 – CO2 emissions of EV charging as a function of CO2 price.

again. Another noteworthy feature is that in both cases the differences in emissions between night charging and peak charging vanishes when more than 10GW of wind is installed. This can be understood by realizing that the probability distribution of the residual system load (electricity demand minus wind generation) of these two cases will approach each other with increasing stochastic generation. The modest change in system load due to EV charging is completely offset by the much larger changes caused by wind generation.

Effect of CO_2 price

Fig. C.4 shows the relation between CO_2 price and EV charging emissions for the different charging patterns and portfolios. For the Dutch portfolio, we observe that there is only a noticeable effect for CO_2 prices higher than 20-25 €/ton. An explanation for this can be found in the difference between coal and gas prices. In Fig. C.1 we observe that coal is about 20 €/MWh cheaper than gas, and emits about 1 ton/MWh. So, only a CO_2 price higher than 20 €/ton will start shifting the coal plants in the merit order. For higher CO_2 prices the effect is modest. For the alternative portfolio, there is immediately a large effect noticeable. The reason for this is that already with low CO_2 prices, nuclear and lignite plants will shift in the merit order and these are exactly the two types of plants that have the largest difference in CO_2 emission.

These results also suggest that with low CO_2 prices, demand response strategies, i.e. shifting load to times with low system demand, might actually lead to higher emissions. As long as the most polluting generation technologies are first in the merit order, any strategy with the aim of shifting load to off peak periods will hence increase the use of the most polluting plants and lead to an increase in CO_2 emissions.

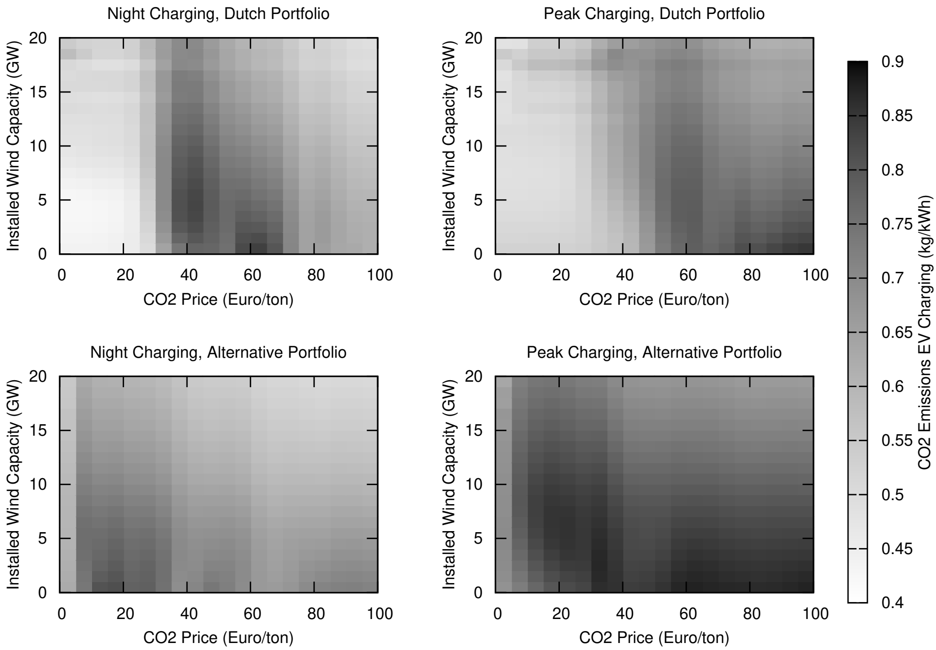


Figure C.5 – CO_2 emissions as a function of CO_2 price and installed wind capacity for both peak and night charging, and both portfolios.

Combined effects

In the previous sections we have shown how different aspects influence CO_2 emissions of EV charging. It is instructive to also see the combined effect of all these aspects. Fig. C.5 essentially contains all information we have presented so far. An important conclusion based on this figure would be the strong sensitivity of the emissions for every single aspect we have considered. It is, however, especially the combination of aspects that determines the exact numbers. This would make any prediction one does about the future emissions of EV charging very difficult. The range in which the CO_2 emissions of EV charging can be found is approximately from 0.4 to 1.4 kg/kWh, or a factor of 3.5.

Conclusions

The most important overall finding from the work presented in this appendix is that CO_2 emissions due to electric vehicle charging are determined in a sometimes counterintuitive way by a combination of the merit order and the timing of charging, because these determine which plants are dispatched for charging the EVs. Using the average CO_2 intensity of electricity generation to estimate the emissions caused by charging electric vehicles can thus lead to imprecise outcomes. The emissions of charging electric vehicles depend strongly on the time of day of charging, the generation portfolio, the amount of installed wind power and the price of CO_2 . With the most-polluting plants being first in the merit order, demand response causing a shift in load to off-peak periods will lead to higher CO_2 emissions.

Furthermore, it was found that emissions of EV charging may range between 0.4 and 1.4 kg/kWh. With an EV driving efficiency range of 0.15-0.2 km/kWh, this would translate to 60-280 g/km. Compared with the typical emissions of modern conventional gasoline vehicles, that are around 130 g/km, switching to electric mobility does by no means guarantee a large reduction in greenhouse gas emissions. A much large share of RES combined with clean dispatchable fossil fuel generation will be needed to achieve this.

Appendix D: Synthetic driver profiles

This appendix describes the method that was used to convert the driver data that originates from [29] to a set of aggregated driver profiles. The reason to use these synthetic profiles is that the various optimization problems that have been used throughout this thesis are computationally only tractable with a limited amount of drivers. The number of drivers still leading to reasonable computation times was found to be in the order 10-50 drivers, depending mainly on the time-horizon of the optimization. Given this relatively low number, it was found that random sampling of the dataset resulted in too large deviations from the average numbers, so a method of constructing aggregate driver profiles that nonetheless reflect the actual distributions was chosen. The method that has been used is a slightly adapted version of the K-means clustering algorithm, which we describe briefly below. More details on this algorithm can e.g. be found in [113].

K-means clustering

In words, the central idea behind K-means clustering is to assign datapoints to a cluster (a group of datapoints) based on the Euclidean distance of the point to the mean of the cluster. After the point has been assigned, new cluster means are computed and the algorithm proceeds to the next datapoint.

An N-dimensional point is denoted as $\mathbf{x}$ with x_i denoting its N components. The 'distance' between two points $\mathbf{x}$ and $\mathbf{y}$ can be defined in various ways, but here (and in most versions of the standard K-means algorithm) we use the squared Euclidean distance defined as

$$d(\mathbf{x}, \mathbf{y}) = \frac{1}{2} \sum_i (x_i - y_i)^2 \tag{1}$$

The mean of cluster k is denoted as $\mathbf{m}^{(k)}$. As initialization, the cluster means are chosen to be equal to N randomly selected samples. The algorithm consists of an assigment and an update step. In the assignemnt step, a datapoint $\mathbf{x}^{(n)}$ is assigned to a cluster $\hat{k}^{(n)}$ according to:

$$\hat{k}^{(n)} = \arg\min_k \{d(\mathbf{x}^{(n)}, \mathbf{m}^{(k)})\} \tag{2}$$

i.e. find the cluster whose mean has the lowest squared Euclidean distance to the datapoint.

In the update step, the new cluster means are computed by

$$\hat{\mathbf{m}}^{(k)} = \frac{1}{N_k} \sum_{\mathbf{x}^{(n)} \in \mathcal{K}^{(k)}} \mathbf{x}^{(n)} \tag{3}$$

where N_k denotes the number of datapoints in cluster k and $\mathcal{K}^{(k)}$ denotes the set of all observations in cluster k. The algorithm, which can be shown to always converge (see [113]), stops if no more changes occur in the assignment step.

Adapted method for equal cluster sizes

For the purpose to use the synthetic driver profiles in the optimization formulations used in this thesis it is convenient to work with equal cluster sizes (the number of datapoints in each cluster) $\overline{N}$. This allows the profiles to be scaled easily to represent an aggregated number of vehicles. We have adapted the method in a pragmatic way to obtain equal cluster sizes. The idea is simply to redistribute the overpopulated clusters (i.e. with more than the predefined cluster size) to the underpopulated clusters, again based on minimizing the squared Euclidean distance to it. This step is performed after each loop through all the datapoints and after the redistribution step the new cluster means are calculated accordingly.

The redistribution steps can be described as follows:

Find set of overpopulated clusters $k^+$with $N_k > \overline{N}$. The underpopulated clusters are k^-.

For all $k \in k^+$ find the $N_k - \overline{N}$ datapoints with the largest Euclidean distance to the cluster mean. Denote this set of datapoints $\mathcal{RD}$

For all $\mathbf{x}^{(n)} \in \mathcal{RD}$ assign to new cluster k according to $\hat{k}^{(n)} = \arg\min_{k^-}\{d(\mathbf{x}^{(n)}, \mathbf{m}^{(k^-)})\}$ and update k^- after each new assigment

Repeat untill $k^- = \emptyset$

Because this procedure has no guaranteed convergence, a heuristic stopping criterion based on the number of changes in the assignment step of the K-means algorithm (not the assignment step during the redistribution steps) was used.

Application to driver data

The original driving data that has been used consists of approximately 18.000 individual drivers and is described more extensively in chapter 2 of this thesis. Three parameters were considered relevant for our purposes: first departure time from home, last arrival time at home and distance driven that day. The datapoints are thus three-dimensional and, furthermore, we have chosen a number of 25 clusters.

The algorithm was found to converge to an alternating state where approximately 50 datapoints (i.e. less than 0.3% of the total) were alternatively assigned to different

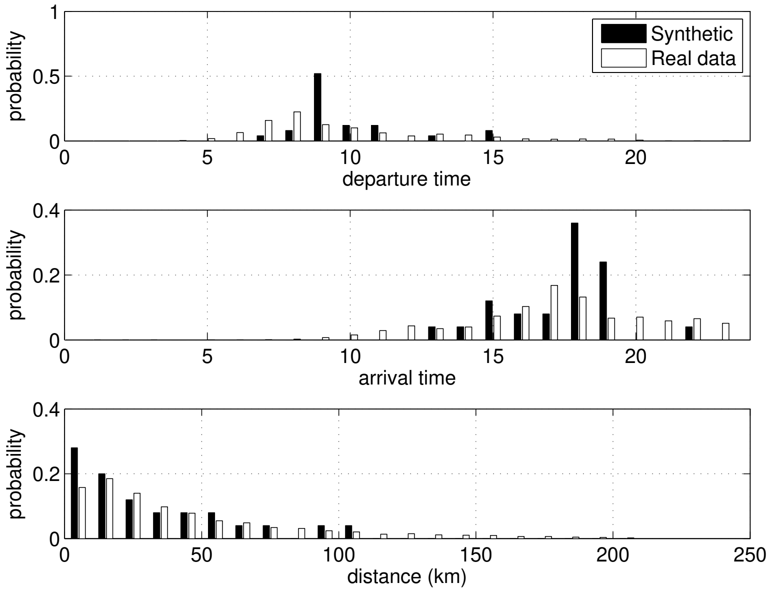


Figure D.1 – Comparison of probability distributions of home departure time, home arrival time and daily driven distance between the original dataset and the synthesized dataset

clusters. After reaching this state the algorithm was stopped manually and the remaining datapoints were discarded.

The resulting set of driver profiles is given in Table D.1. To compare the synthesized driver set with the original dataset, we plot the probability distributions of the three different parameters in Fig. D.1. We observe that the distributions have roughly a similar shape. However, due to the small number of drivers in the synthesized set, there are unevitably some differences between the distributions. Most notably, the departure and the arrival times seem to be more centered towards the average departure and arrival times. Still, the main characteristics of the driving data have been preserved to a reasonable extent and we consider the synthetic profiles a better alternative than randomly sampling 25 drivers from the original data.

Table D.1 – Synthetic driver profiles

Driver	Departure time	Arrival time	Distance (km)
1	10.11	13.12	3.1
2	9.26	18.34	35.2
3	9.31	15.21	14.5
4	8.41	14.26	7.8
5	11.21	18.54	16.8
6	9.13	15.27	10.9
7	9.16	16.50	24.8
8	10.27	15.20	5.7
9	9.06	18.33	50.8
10	11.07	18.58	21.7
11	11.31	19.11	28.2
12	9.26	19.25	109.2
13	13.21	18.26	11.8
14	9.16	18.45	58.8
15	9.07	17.17	31.0
16	15.04	19.22	3.2
17	9.13	18.25	40.1
18	9.11	18.59	77.0
19	10.11	18.46	45.2
20	9.40	19.22	65.9
21	7.38	17.58	4.3
22	8.38	22.17	4.5
23	9.08	16.01	19.5
24	9.09	19.24	91.8
25	15.09	19.48	7.9

Appendix E: Cold storage as another resource for demand response

This appendix is based on the work described in [102]

This thesis, as its subtitle suggests, explores the potential of flexible electricity demand. So far, though, we have only considered EV demand as the main source of flexibility. In principle, other types of electricity demand could offer demand response services as well. Similar types of optimization problems can be formulated in terms of similar objectives described earlier in this thesis, either related to price or to reduce network loads or losses. In this appendix we briefly describe another type of responsive demand: a cold storage warehouse. Here we only summarize the work that has been described in more detail in [102], and we briefly touch upon the similarities and difference with the EV charging optimization.

A cold storage warehouse is basically a huge refrigerator where goods are stored at very low temperatures. In a simple approximation of temperature dynamics, an equation for the cold store temperature T_c in terms of the ambient temperature T_a and cooling power P_c can be derived. It reads, in discrete time-step k:

$$T_c[k+1] = (1-a)T_c[k] + aT_a[k] - bP_c[k] \tag{4}$$

with

$$a = \frac{UA\Delta t}{C_p} \tag{5}$$

$$b = \frac{\eta\Delta t}{C_p} \tag{6}$$

where the different symbols, and their values used in an example simulation, are listed in Table E.1. This equation is analogous to Eq. 2.8 that describe the energy content of an EV battery. Indeed, instead of electro-chemical energy stored in a battery we now have heat (or rather: cold) stored in the cold storage warehouse - they are of course the state variables (a term often used in control theory) that physically describe the system. The ‘sink’ term is now given by $a(T_c[k] - T_a[k])$,

Table E.1 – Physical and simulation parameters

	Value	Unit	Description
C_p	2500	kWh/K	Cold store heat capacity
UA	20	kW/K	Heat transfer coefficient between cold store and ambient
Δt	0.25	h	Simulation time-step
η	3	-	Cooling power efficiency
$P_{c,min}$	0	kW	Minimum cooling power
$P_{c,max}$	2000	kW	Maximum cooling power
PV_{max}	2000	kW	Installed PV capacity
T_{max}	-18	°C	Temperature limit of cold store
T_a	15	°C	Ambient temperature

whereas in the case of the EVs energy was 'leaking' through the term that described battery discharge due to driving $\eta_d L_k$. The 'source' is now the cooling power P_c whereas in the EV case it was the charging power P_{EV}.

An evident optimization strategy would be to minimize the total costs for cooling, while maintaining the cold store temperature within limits. The optimization formulation reads:

$$\min_{P_c[k]} \sum_{k=1}^{N_k} \lambda[k] P_c[k] \tag{7}$$

$$\text{s.t.} \quad T_{c,min} \leq T_c[k] \leq T_{c,max} \tag{8}$$

$$P_{c,min} \leq P_c[k] \leq P_{c,max} \tag{9}$$

$$T_c[k+1] = (1-a)T_c[k] + aT_a[k] - bP_c[k] \tag{10}$$

This formulation is almost completely identical to the EV charging optimization formulation given in Eqs. 2.9 to Eq. 2.12, except for the dynamic equation that is slightly different.

Case study simulation

As an illustration of how the flexibility of a cold storage warehouse can be exploited, we consider the setting depicted in Fig. E.1. The cold store has PV production on the same site, and it can both withdraw power from the grid at a (time-varying) cost $C_{in}[k]$ and feed back against a certain tariff $C_{out}[k]$. In many countries, and presumably even more so in the future, tariffs for consuming are higher than for delivering energy to the grid. The challenge is thus to find the optimal cooling schedule that maximizes the profits of energy delivery minus the cost of purchase. The objective function is hence given by:

$$\min_{P_{in}[k], P_{out}[k]} \sum_{k=1}^{N_k} C_{in}[k] P_{in}[k] - C_{out}[k] P_{out}[k] \tag{11}$$

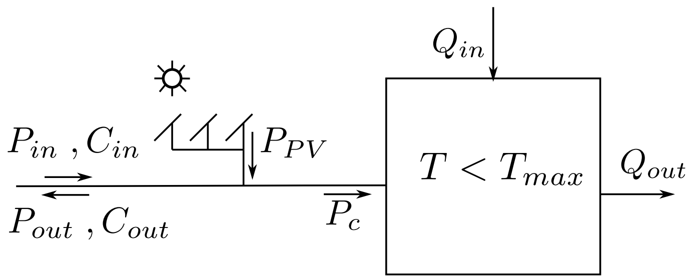


Figure E.1 – Schematic representation of the cold store with installed PV capacity. The cold can withdraw power from the grid P_{in} at a cost C_{in} and feed power P_{out} into the grid for a price C_{out}

If no electricity can be stored on site, we have an extra equation to link the PV power and the in- and outflows of electricity:

$$P_c[k] = P_{PV}[k] + P_{in}[k] - P_{out}[k] \tag{12}$$

Together with the constraints described above, these equations are the complete optimization formulation of the problem. The main goal of the work described in [102] was to assess the effect of different electricity tariff structures on cold storage electricity demand. Five different tariff structures were studied, see Fig. E.2.

The price scenarios range from a flat tariff to a real-time price, modeled on the basis of wholesale prices. In scenario E, a real-time price that would be observed in a system with a large amount of solar power is modeled.

Fig. E.3 shows the optimization results for what could be considered the most extreme cases: the flat tariff without a feed in penalty (3(a)) and the real time tariff (with feed-in penalty) based on wholesale prices in a high solar system. The PV power is modeled so as to represent two sunny and two cloudy days, see the upper panels of Fig. E.3; the ambient temperature is assumed to be constant at 15 °C. One observes how in the flat tariff case, the cooling power is constant and keeps the cold storage temperature at exactly the upper temperature limit, which makes sense because the 'heat loss' to the environment is proportional to the temperature difference $T_c - T_a$.

In the case of the real time wholesale based tariff, a markedly different cooling trajectory is optimal. Here it pays off to use all PV power for cooling during the sunny days and 'ride through' the cloudy days without having to buy electricity from the grid. This is at the expense of higher thermal losses, of course, but the price differences make it worthwhile.

The results for the other tariff cases are listed in Table E.2. One observes how, depending on the tariff, markedly different outcomes are found in terms of the amounts of energy ands maximum power. From a network point of view, for instance, one could argue that smaller maximum power withdrawal or feed-in are beneficial - something that is not properly incentivised in many tariffs.

The economic value of the look-ahead energy management strategies can be evaluated by considering the difference with the uncontrolled cooling schedule (this

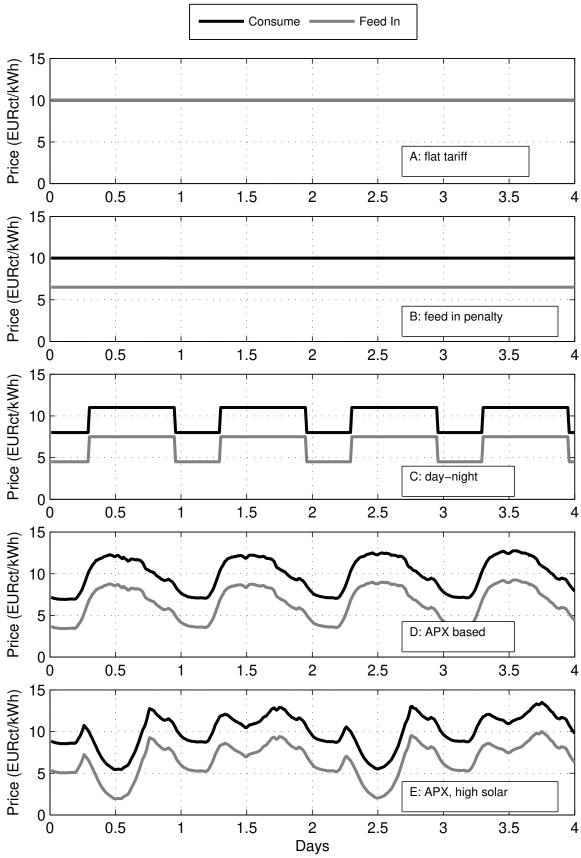
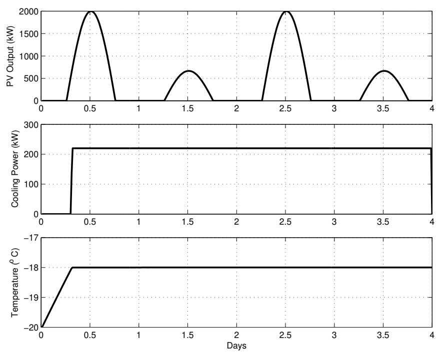
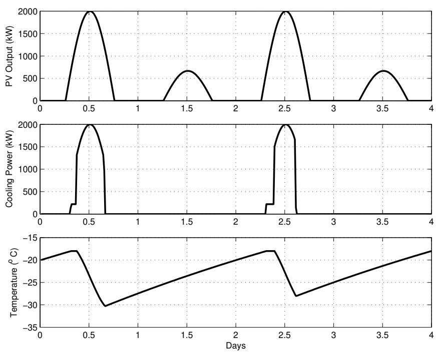


Figure E.2 – Different price scenarios.



(a) Flat tariff



(b) Wholesale price based - high solar

Figure E.3 – PV production, optimal cooling trajectory and cold storage temperature for two different tariffs.

Table E.2 – Overview of some relevant simulation results.

Price case	Profit (EUR)	Cooling Energy Used (MWh)	Energy Withdrawn (MWh)	Energy Fed In (MWh)	Maximum Power Withdrawn (kW)	Maximum Power Fed In (kW)
A: flat tariff	8500	19.4	9.9	31.2	220	1780
B: flat tariff, feed-in penalty	5310	20.3	0	20.4	0	1780
C: day-night tariff	6220	19.7	5.1	26.2	220	1780
D: APX based real time	7960	20.7	18.9	38.9	2000	2000
E: APX based high solar	4960	22.5	0	18.2	0	1504

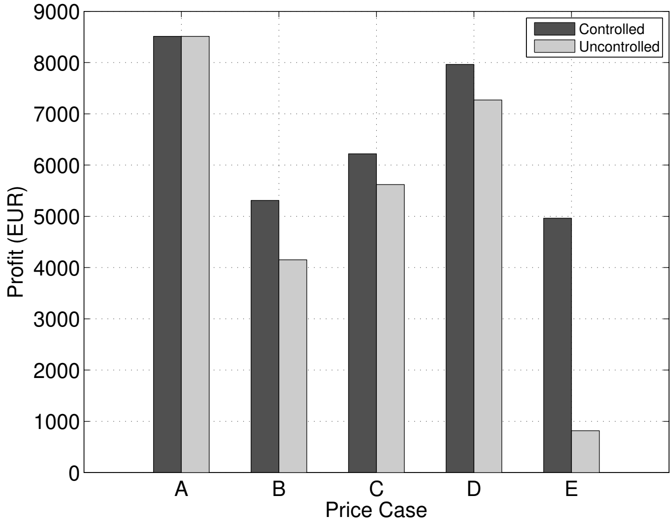


Figure E.4 – Comparison of the profits between the different price cases and the effect of the optimization.

would be the same as in scenario A, since this minimizes the total cooling energy needed). Fig. E.4 shows these differences. Scenario E shows the highest value for the look-ahead optimization, which can be understood by the specific combination of PV production and time varying prices. If these happen to coincide, there is most incentive in using all locally produced energy.

The example treated in this appendix shows the similarity between EV load management and another form of demand response. In the end, it is the physical properties of the system under consideration that determine the economic potential. In this perspective, it is interesting to note that the physics of the cold storage are essentially determined by two parameters: its thermal mass, represented by C_p and the thermal leakage contained in UA. The ratio of these two defines a certain fundamental 'time constant' associated with the system. In this case we find for this time constant a value of 125 hours, but for example a household refrigeration system a much smaller time constant is found, roughly in the order of several hours. This time constant determines, to a large extent, how flexible the system is, i.e. how long the consumption of energy can be postponed and how much value can be created by looking ahead and awaiting favorable conditions.

In the case of EVs, on the other hand, a similar time constant can be determined by comparing the battery capacity with the typical daily driving energy needed. In the simulations considered in this thesis that amounted to approximately 4 days, so a similar order of magnitude. This, to a large extent, explains the suitability of EVs for demand side management compared to other forms like heating and cooling of residential buildings.

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Nomenclature

Symbols

α_k	Non-EV dependent part of electricity price at time-step k
β	Sensitivity of electricity price to EV demand
Δt	Simulation time-step
η_c	Charging efficiency
η_d	Driving efficiency
λ_k	Electricity price at time-step k
μ_k	Network tariff at time k
d_{ik}	Battery discharge due to driving of EV i at time-step k
$E_{EV,ik}$	Energy content of (the battery of) EV i at time-step k
$E_{EV_{max},i}$	Maximum energy content of EV i
$E_{EV_{min},i}$	Minimum energy content of EV i
F_{Lk}	Line flow in transmission line L at time-step k
g	Simultaneity factor
$H_{in,jk}$	Water inflow into pumped hydro unit j at time-step k
H_{jk}	Water level of pumped hydro unit j at time-step k
$H_{max,j}$	Maximum water level of pumped hydro unit j
$H_{min,j}$	Minimum water level of pumped hydro unit j
I_l	Current flowing through in line l
K_L	Capacity of transmission line L
L_{ik}	Distance driven by EV i at time-step k
N_G	Total number of generators

N_H Total number of hydro generators

N_k Number of time-steps

N_{EV} Total number of EVs

P_l Real power flowing through line l

$P_{batt,ik}$ Power flow into EV battery i at time-step k

$P_{D,k}$ Total electricity demand at time-step k

$P_{D0,k}$ Electricity demand (without EV demand) at time-step k

$P_{EV,ik}$ Power flow into EV i at time-step k

$P_{EV,k}$ EV demand at time-step k

$P_{EV_{max},i}$ Maximum charging power of EV i

$P_{EV_{min},i}$ Minimum charging power of EV i

$P_{G,nk}$ Power output of generating unit n at time-step k

$P_{G_{max},n}$ Maximum power output of generating unit n

$P_{G_{min},n}$ Minimum power output of generating unit n

$P_{H_{max},j}$ Maximum power output of pumped hydro unit j

$P_{H_{min},j}$ Minimum power output of pumped hydro unit j

P_{Hjk} Power output of pumped hydro unit j at time-step k

$P_{loss,l}$ Power loss in line l

Q Amount of charge inside a battery

Q_0 Nominal battery capacity

R_l Resistance of line l

SoC State of charge (of a battery)

u_{nk} Binary variable expressing if unit n is on-line at time-step k

V_C Value of EV charging control

V_T Value of transmission capacity

V_{T+C} Value of both transmission capacity and EV charging control

y_{nk} Binary variable expressing if unit n is in start-up mode at time-step k

z_{nk} Binary variable expressing if unit n is in shut-down mode at time-step k

Acronyms

CHP	Combined heat and power
CPM	Charge point manager
DSO	Distribution system operator
EV	Electric vehicle
HV	High voltage
LV	Low voltage
MV	Medium voltage
MV-D	Medium voltage distribution
MV-T	Medium voltage transmission
NPV	Net present value
PHEV	Plug-in hybrid electric vehicle
PV	Photo-voltaic
RES	Renewable energy sources
RoR	Run-of-river
ToU	Time-of-use
TSO	Transmission system operator
V2G	Vehicle-to-grid
VOLL	Value of lost load

Summary

Introduction and problem statement

Environmental, economic and geo-political concerns continue to drive the decarbonisation of many economies worldwide. In the power sector this is leading to a sharp increase in renewable energy sources (RES). The most important RES, wind power and solar (PV) power, are, however, fundamentally different types of electricity production compared to conventional fossil fuel based generation: their output is variable, less dispatchable and prone to forecast errors. One possible paradigm to ease the integration of RES is to involve the potential flexibility on the demand side of the electricity system. Currently, however, the amount of flexible electricity demand is limited. Electric vehicles, by contrast, provide a source of flexibility of significant magnitude. Moreover, when powered by green electricity, they pave the way for strong reductions in greenhouse gas emissions in the transport sector. EVs and RES are therefore natural candidates to co-exist in a powerful synergy.

Nonetheless, the large increase in electricity use associated with a large scale adoption of EVs could also require significant infrastructure investments. Here, too, the flexibility of EVs holds an economic potential because it could reduce the required network investments. In liberalized power systems, however, generation and retail on the one hand, and transport and distribution of electricity on the other hand, are separated activities concerning different actors. The flexibility of EV charging can provide a value with respect to all these activities, but the associated actor objectives may be conflicting. This thesis thus aims to answer the following research question:

How can the flexibility of EV charging best be utilized in multi-actor power systems with high shares of renewable energy sources?

To answer this question we will first explore controlled EV charging from the point of view of the distribution networks and from the perspective of integrating variable RES. Hereafter we combine both perspectives and investigate mechanism to allign the network and generation related objectives.

Research methods, results and insights

Different perspectives on EV charging

In this thesis we study the role of EVs both from a network point of view and in the light of RES integration in unbundled and liberalized power systems. We therefore analyse the most important technological, economic and institutional aspects of these power systems and relevant EV characteristics to obtain a modelling framework that is used in this thesis.

In the unbundled and liberalized power systems of many western countries, electricity prices emerge as the result of supply and demand bids, and according to basic economic principles, wholesale prices tend to be correlated with demand: high prices in periods of peak demand. RES alter this dynamic to some extent, because they lower prices in periods with high RES output. For an aggregator that aims to minimize the energy costs of charging a fleet of EVs, it is beneficial to shift the EV demand to the periods with low prices. Price-responsive EV demand therefore has the positive effect of creating a flatter residual load profile and dampening price fluctuations. From the perspective of a distribution system operator (DSO), EV charging would be scheduled differently, since the DSOs are regulated such that they have incentives to reduce costs. This would translate in an objective to lower energy losses and avoid unnecessary investments in distribution assets, which means that peaks on local network load need to be avoided.

Comparing typical EV battery characteristics such as energy content and power limits with the typical driving patterns people exhibit, one finds that there is a significant opportunity to postpone the charging process. Using a simple linear model of EV battery dynamics and e.g. electricity prices or network load we can formulate EV charging as an optimization problem whose objective function depends on what aspect of the power system and its associated actor are targeted. This thesis explores the potential of this flexibility first from the point of view of the distribution networks and then from the point of view to lower generation costs, either directly, or through the signal provided by the wholesale electricity price. Moreover, we also combine these perspectives and analyze how and when the network and generation related objectives can be conflicting and investigate possible mechanisms to align them. We assume simplified institutional arrangements where either EVs are modeled to directly interact with the system or they are represented by an aggregator as an intermediate party.

Distribution networks impacts

In chapter 4 we study the potential of controlled EV charging with respect to the electricity distribution system. From this perspective, an EV charging strategy that shifts the bulk of the energy transfer to the night hours when network load is low, greatly reduces the extra peak load caused by EV charging that would result from an uncontrolled charging strategy. Different EV charging profiles, controlled and uncontrolled, are superimposed on existing network load profiles to assess the impacts on different types of distribution assets. It was found that in the uncontrolled charging scenarios the extra EV load would lead to a significant amount of overloaded assets, and the effect is most prominent on the MV/LV transformer level. In the controlled EV charging scenario almost all of the extra replacements compared to the reference case without any EVs can be avoided. The financial consequences of the different scenarios have been evaluated by considering the net present value of the annuitized investment costs and the costs for energy losses. The controlled charging scenario proved to have an approximately 20% lower NPV than the uncontrolled scenario. Whereas the energy losses dominate the total cost figures, the differences between the scenarios are largely caused by the replacement costs. Furthermore, the costs related to MV-cables were found to be most prominent compared to that of the MV/LV transformers and HV-substations.

Generation costs and interrelations between controlled EV demand and cross-border transmission

The objective of chapter 5 is to investigate the potential of EV responsive demand with respect to lowering marginal generation costs in systems with a high penetration of RES. Furthermore, we look at interdependencies between controlled electric vehicle charging and cross-border transmission capacity - two paradigms that are usually seen as important in facilitating RES integration. We extend a unit commitment model with electric vehicle charging power as decision variable and we study a conceptual two node system based on German data with wind power in one node and solar power in the other node. The results show that EVs lead to significant cost reduction because they shift demand to periods of high wind and/or solar power and limit the use of expensive gas plants. For an expected renewable energy penetration scenario for 2025, controlled charging and extra transmission capacity can be considered substitute technologies - they both lead to certain cost reduction, more or less independent of each other. We conclude, however, that with a higher renewable energy scenario, the demand for energy arbitrage increases and the two technologies become complementary in the sense that there combined potential is higher than the sum of their individual effects. The main reason for this is that cross-border transmission capacity is needed to transport power to where the electric vehicles can absorb it. These insights are relevant in the light of European renewable energy targets towards the year 2050.

Aligning distribution network objectives and price-responsive demand

When EVs act as responsive loads that increase demand when electricity prices are low, they could cause high peaks in network load. The effect becomes more prominent in high RES scenarios, because a high penetration of stochastic generation leads to a weakened correlation between wholesale electricity prices and network demand. Chapter 6 therefore investigates possible congestion management mechanisms for price-responsive electric vehicle demand in electricity distribution networks. It was shown that application of some form of congestion management is justified, because limiting the EV load to available network capacity leads to a negligible increase in energy costs. Simple grid tariffs based on network load were found to make the problem worse compared to the base case scenario of flat grid tariffs. An optimal dynamic grid tariff that is unilaterally determined by the DSO leads to desirable outcomes but is difficult to determine under real life conditions where uncertainty plays a role. A distribution grid capacity market - an iterative approach where DSO and aggregator sequentially exchange dynamic tariffs and resulting electricity demand - converges to a final price and charging schedule, but requires a complex IT infrastructure and has a heavy computational burden. Advance capacity allocation is more straightforward to implement in the case of a single aggregator, but there remain important issues related to the allocation of the capacity between multiple aggregators and the inter-temporal constraints of the EVs. There thus exists a trade-off between the complexity and efficiency of a congestion management mechanism which should be subject of further investigation that takes uncertainty into account.

A refined view on EV charging

Chapter 7 aims to connect the different elements discussed in the preceding chapters. Most notably, we analyze differences between a centralized approach in which generation costs are minimized and a decentralized approach where EV charging costs are minimized based on wholesale prices. It was found that aggregators who schedule a very large part of EV demand can exert market power by influencing wholesale prices. If there is enough competition between aggregators, the aggregated EV demand profile converges to the socially optimal profile.

Furthermore, we show how the value of controlling EV demand depends on various aspects such as the control horizon of the optimization, inter-temporal constraints of generation units and the availability of EVs for charging. These analyses suggest that also under milder assumptions regarding the predictability of electricity prices and EV behavior, the value of controlling EV charging is still high, and there is still a need for congestion management to avoid unnecessary peaks in network demand. Analyzing the effects of cost minimizing EVs on a large number of distribution networks confirmed that the peaks caused by price-responsive EV load leads to a significant amount of extra costs related to network investments.

Conclusions

The thesis addresses *how the flexibility of EV charging can best be utilized in multi-actor power systems with high shares of renewable energy sources.* The answer this question can be summarized as follows: the two important perspectives from which controlled EV charging can add most value are its ability to be shifted in time according to fluctuating RES output on the one hand, and to avoid peaks in network demand to defer or postpone network investments on the other hand. With flat network tariffs and wholesale prices that will be influenced strongly by fluctuating RES output, price responsive EV demand can, ironically, lead to even higher demand peaks than uncontrolled EV charging. The required network reinforcements are costly and unnecessary because limiting the load to free network capacity through an efficient congestion management mechanism has negligible additional energy costs. There are various congestion mechanisms possible to allign the cost minimizing EVs with network constraints, either based on shadow prices associated with the network constraints or an ex-ante allocation of free network capacity, but in both approaches there exists a trade-off between simplicity and economic efficiency. All schemes, however, seem to have in common that the function of the DSO is extended beyond its current role. A clean and intelligent power system might therefore require a re-thinking of the rules and roles in today's unbundled power systems. When objectives related to different functions of the electricity system are aligned in such intelligent IT enabled systems, demand response and EVs in particular can play a key role in the transition to a cleaner energy system.

Samenvatting

Introductie en probleemstelling

Milieu-gerelateerde, economische en geopolitieke zorgen blijven de drijvende kracht achter decarbonisering van economiën wereldwijd. In de elektriciteitssector leidt dit tot een scherpe toename van duurzame energiebronnen. De meeste belangrijke duurzame energiebronnen, wind- en zonne-energie, zijn echter fundamenteel andere vormen van elektriciteitsproductie dan de conventionele centrales op basis van fossiele brandstoffen: hun productie is variabel, minder goed regelbaar en onderhevig aan voorspellingsfouten. Eén van de mogelijke paradigma's om de integratie van duurzame energie te vergemakkelijken is om de potentiële flexibiliteit aan de vraagkant van het elektriciteitssysteem aan te spreken. Momenteel is de hoeveelheid flexibele elektriciteitsvraag echter gering. Elektrische auto's (*Electric vehicles* EVs) bieden daarentegen een bron van flexibiliteit van aanzienlijke grootte. Als ze door duurzame bronnen van stroom worden voorzien, banen ze bovendien de weg voor forse reducties van broeikasgassen in de transportsector. Elektrische auto's en duurzame energie zijn daarom logische kandidaten om in een sterke synergie te co-existeren.

Desalniettemin kan de grote toename in elektriciteitsgebruik door de grootschalige introductie van EVs ook aanzienlijke investeringen in infrastructuur vereisen. Ook hier bevat de flexibiliteit van EVs een economisch potentieel omdat het de benodigde netwerkinvesteringen kan verlagen. In geliberaliseerde en gesplitste[1] elektriciteitssystemen zijn productie en handel van elektriciteit aan de ene kant en transport en distributie aan de andere kant gescheiden activiteiten die verschillende actoren toebehoren. De flexibiliteit van het laden van EVs kan een waarde voor al deze actoren vertegenwoordigen, maar de bijbehorende doelstellingen kunnen onderling strijdig zijn. Dit proefschrift probeert daarom de volgende onderzoeksvraag te beantwoorden:

Hoe kan de flexibiliteit van EVs het best worden benut in multi-actor elektriciteitssystemen met een hoog aandeel duurzame energie?

Om deze vraag te beantwoorden zullen we eerst het gestuurd laden van EVs vanuit het oogpunt van de distributienetten bestuderen, en dan vanuit het perspectief van de integratie van duurzame energie. Hierna combineren we beide perspectieven en onderzoeken mechanismen om de doelstellingen vanuit de oogpunten van netwerk en duurzame energieproductie op een lijn te brengen.

[1] *Gesplitst* verwijst naar de splitsing van commerciële activiteiten en netwerkbeheer.

Onderzoeksmethode, resultaten en inzichten

Verschillende perspectieven op het laden van elektrische auto's

In dit proefschrift bestuderen we de rol van EVs vanuit een netwerkoogpunt en in het licht van integratie van duurzame energie in geliberaliseerde elektriciteitssystemen. Daarom analyseren we eerst de belangrijkste technische, economische en institutionele aspecten van deze systemen en de relevante karakteristieken van EVs om een modelleerraamwerk dat in dit proefschrift gebruikt wordt te verkrijgen.

In de gesplitste en geliberaliseerde elektriciteitssystemen van veel westerse landen, ontstaan elektriciteitsprijzen als het gevolg van biedingen van vraag en aanbod. Volgens economische basisprincipes zijn de prijzen gecorreleerd met de vraag: hoge prijzen ten tijde van piekvraag. Duurzame energiebronnen veranderen deze dynamiek in zeker mate, omdat ze de prijzen drukken op momenten van veel duurzame productie. Voor een aggregator die als doel heeft om de energiekosten van het laden van een groep EVs te minimaliseren is het dus gunstig om de EV elektriciteitsvraag te verschuiven naar periodes met lage prijzen. Prijs-responsieve vraag van EVs heeft daarom een positief effect doordat het zorgt voor een vlakker netto belastingsprofiel en een dempende werking op fluctuerende prijzen. Vanuit het perspectief van een distributienetbeheerder (DNB) zou het laden van EVs anders gepland worden, omdat DNBs op zodanige wijze gereguleerd zijn dat ze een prikkel hebben om kosten te reduceren. Dit zou zich vertalen naar een doelstelling om de de energieverliezen te verlagen en onnodige investeringen in de netten te vermijden, wat erop neerkomt dat pieken in de lokale netbelasting voorkomen dienen te worden.

Impacts op de distributienetwerken

In hoofdstuk 4 bestuderen we het potentieel van het gestuurd laden van EVs met het oog op het distributienetwerk. Vanuit dit perspectief zorgt een oplaadstrategie die de bulk van de energie-overdracht naar de nacht verplaatst als de netbelasting laag is voor een sterke reductie van de extra piekbelasting die het ongecontroleerd opladen van EVs tot gevolg zou hebben. Verschillende EV laadprofielen, gecontroleerd en ongecontroleerd, worden bij bestaande netwerkprofielen opgeteld om de impact op verschillende typen netwerkcomponenten te evalueren. Er blijkt dat in de ongecontroleerde scenario's de extra EV belasting tot een significant aantal overbelaste componenten zou leiden. Dit effect is het meest prominent op het niveau van de MS/LS-transformatoren (middenspanning/laagspanning). In het controleerde scenario kunnen bijna alle extra vervangeningen t.o.v. het referentie-scenario zonder EVs voorkomen worden. De financiële consequenties van de verschillende scenario's zijn geëvalueerd op basis van de netto contante waarde van de annuïteiten van de vervangingskosten en de kosten voor energieverliezen. Het gecontroleerde laadscenario bleek een ongeveer 20 % lagere netto contante waarde te hebben de ongecontroleerde scenario's. Hoewel de kosten van energieverliezen de totale kostenplaatjes domineren, worden de verschillen tussen de scenarios vooral veroorzaakt door de vervangingskosten. Ook bleek dat de kosten gerelateerd aan de middenspanningskabels dominant waren t.o.v. de kosten voor laagspanningstransformatoren en transformatorstations van hoogspanning naar middenspanning.

Productiekosten van elektriciteit en de onderlinge relatie tussen en het gestuurd laden van elektrische auto's en grensoverschrijdende transmissie

Het doel van hoofstuk 5 is om te onderzoeken in hoeverre de prijs-responsieve vraag van EVs de marginale productiekosten van elektriciteit kan verminderen in een systeem met een hoog aandeel duurzame energie. Verder kijken we naar de onderlinge afhankelijkheden tussen het gestuurd laden van EVs en grensoverschrijdende transmissie-capaciteit - twee paradigma's die als belangrijk worden gezien in het faciliteren van de integratie van duurzame energie. We breiden een *unit commitment*[2] model uit met het opladen van EVs als beslissingsvariabelen en we bestuderen een conceptueel systeem van twee knooppunten. Dit systeem is gebaseerd op data van het Duitse systeem en heeft windenergie in het ene knooppunt en zonne-energie in het andere. De resultaten laten zien dat gestuurde EVs tot een significante kostenbesparing leiden doordat de elektriciteitsvraag naar de periodes met veel wind- en zonne-energie wordt verschoven en zo de inzet van dure gascentrales wordt beperkt. In een scenario voor de penetratie van duurzame energie voor 2025 kunnen het gestuurd laden van EVs en grensoverschrijdende transmissie vooral als substituten worden gezien. Ze leiden beide tot een bepaalde kostenreductie, onafhankelijk van elkaar. Voor een scenario met meer duurzame energie concluderen we echter dat de twee technologiën complementair worden. Hun gezamenlijke potentieel is groter dan de twee afzonderlijk bij elkaar genomen. De belangrijkste reden hiervoor is dat grensoverschrijdende transmissiecapaciteit nodig is om energie te transporteren naar de locatie waar EVs het kunnen absorberen. Deze inzichten zijn relevant in het licht van de Europese doelstellingen voor duurzame energie voor het jaar 2050.

Het op een lijn brengen van doelstellingen t.a.v. distributienetten en prijs-responsieve vraag

Als EVs zich als responsieve belasting gedragen die hun vraag doen toenemen als elektriciteitsprijzen laag zijn, kunnen ze hoge pieken in netwerkbelasting veroorzaken. Dit effect wordt nog prominenter in scenario's met veel duurzame energie, omdat een hoge penetratie van fluctuerende productie leidt tot een verminderde correlatie tussen marktprijzen en netwerkbelasting van elektriciteit. Hoofdstuk 6 onderzoekt daarom mogelijke mechanismen voor congestie-management voor prijs-responsieve vraag van EVs in distributienetten. Er is aangetoond dat het toepassen van een vorm van congestie-management gerechtvaardigd is omdat het limiteren van de vraag van EVs tot de beschikbare netwerkcapaciteit verwaarloosbare extra energiekosten met zich meebrengt. Simpele netwerktarieven bleken het probleem erger te maken in vergelijking met het referentiescenario van vlakke netwerktarieven. Een optimaal dynamisch netwerktarief dat unilateraal door de netbeheerder wordt bepaald leidt tot wenselijke uitkomsten maar is moeilijk te bepalen in de praktijk waarin onzekerheden een rol spelen. Een capaciteitsmarkt voor een distributienet - een iteratieve benadering waarin netbeheerder en EV aggregator sequentieel dynamische tarieven en de resulterende elektriciteitsvraag uitwisselen - convergeert naar een uiteindelijke prijs en een laadschema, maar vereist een complexe ICT infrastruc-

[2]Dit type model wordt gebruikt om de inzet van de elektriciteitscentrales te plannen

tuur en veeleisende computerberekeningen. Het vooraf alloceren van capaciteit is meer rechttoe rechtaan om te implementeren in het geval van één enkele EV aggregator, maar er blijven belangrijke bezwaren bestaan gerelateerd aan het verdelen van capaciteit tussen verschillende aggregatoren en de intertemporele afhankelijkheden van het laden van EVs. Er bestaat dus een trade-off tussen de complexiteit en de effectiviteit van een congestie-management mechanisme die aan nader onderzoek dat onzekerheden meeneemt onderworpen zou moeten worden.

Een verfijnde kijk op het laden van elektrische auto's

Hoofdstuk 7 beoogt de verschillende elementen uit voorgaande hoofdstukken aan elkaar te verbinden. In het bijzonder analyseren we verschillen tussen een gecentraliseerde benadering waarin productiekosten worden geminimaliseerd en een decentrale benadering waarin de laadkosten van EVs geminimaliseerd worden op basis van marktprijzen van elektriciteit. Er blijkt dat aggregatoren die een zeer groot deel van de totale elektriciteitsvraag van EVs plannen marktmacht kunnen uitoefenen door het beïnvloeden van marktprijzen. Als er voldoende concurrentie tussen aggregatoren is, zal het geaggregeerde vraagprofiel van de EVs het sociaal optimale profiel benaderen.

Verder laten we zien hoe de waarde van het gestuurd laden van elektrische auto's van diverse aspecten afhangt zoals de optimalisatiehorizon, intertemporele afhankelijkheden in elektriciteitscentrales en de beschikbaarheid van EVs om te laden. Deze analyses suggereren dat ook onder mildere aannames over de voorspelbaarheid van elektriciteitsprijzen en EV gedrag de waarde van het gestuurd laden nog steeds hoog is, en dat nog steeds de noodzaak tot congestie-management bestaat om onnodige pieken in netbelasting te voorkomen. Het analyseren van de effecten die prijs-responsieve vraag van EVs op een groot aantal distributienetten bevestigde dat de door kosten-minimaliserende EVs veroorzaakte vraagpieken leiden tot een aanzienlijke hoeveelheid extra kosten gerelateerd aan netwerkinvesteringen.

Conclusies

Deze thesis behandelt de vraag *hoe de flexibiliteit van het laden van elektrische auto's het best benut kan worden in multi-actor elektriciteitssystemen met een hoog aandeel duurzame energie.* Het antwoord op deze vraag kan als volgt samengevat worden: de twee belangrijke perspectieven van waaruit het gestuurd laden van EVs de meeste waarde kan toevoegen zijn het vermogen om het laden in tijd te verschuiven al naar gelang de productie van duurzame energie enerzijds, en om pieken in netwerkbelasting te voorkomen om netwerkinvesteringen uit of af te stellen anderzijds. Met de huidige vlakke netwerktarieven en marktprijzen van elektriciteit die sterk door duurzame energie beïnvloed worden, kan op prijs reagerende vraag van EVs ironisch genoeg tot hogere vraagpieken leiden dan ongecontroleerd laden. De benodigde netwerkinvesteringen zijn echter onnodig omdat het beperken van de EV vraag tot de vrije netwerkcapaciteit middels een efficiënt congestie-management mechanisme tot verwaarloosbare hogere energiekosten leidt. Er zijn verschillende mechanismen voor congestie-management mogelijk om kosten-minimaliserende EVs op een lijn te brengen met netwerkbeperkingen. Die zijn ofwel gebaseerd op schaduwprijzen geässocieerd met de netwerkbeperkingen of op het vooraf alloceren van vrije capaciteit, maar in beide benaderingen bestaat er een trade-off tussen eenvoud en economische efficiëntie. Al deze benaderingen lijken echter gemeen te hebben dat de functie van de netbeheerder verder gaat dan zijn huidige rol. Een schoon en intelligent elektriciteitssysteem zou daarom wel eens een heroverweging van de rollen en regels van de huidige gesplitste elektriciteitssector kunnen vergen. Als de doelstellingen met betrekking tot de verschillende functies van het elektriciteitssysteem op één lijn gebracht zijn in dergelijke intelligente, door ICT mogelijk gemaakte systemen, kunnen vraag-respons en EVs in het bijzonder een sleutelrol vervullen in de transitie naar een duurzamer energiesysteem.

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Curriculum vitae

Remco Alexander Verzijlbergh was born on June 10th 1981 in Hellevoetsluis, the Netherlands. He finished his pre-university education at the *Erasmiaans Gymnasium* in Rotterdam in 1999 and commenced his study Applied Physics at Delft University of Technology in 2000. Towards the end of the bachelor program he became interested in atmospheric physics. During his MSc graduation project he studied and published a journal paper on the role of clouds in the dispersion of pollutants through the atmosphere, under supervision of prof.dr. H.J.J. Jonker and dr. T. Heus.

Before receiving the MSc in Applied Physics Remco conducted an internship at Dutch energy company Nuon in 2008, where he worked in field experiments on an experimental micro-grid equipped with solar PV and battery storage. During this period, the company, enforced by the Dutch unbundling law, split into a commercial branch (Nuon) and a regulated network branch (Alliander). After his graduation he continued working for what was now distribution system operator Alliander for several months, before returning to Delft.

In 2009 he started his PhD research on the role of electric vehicles in future power systems in the Energy & Industry group at the faculty of Technology, Policy and Management, under supervision of dr.ir. Z. Lukszo and prof.dr. M.D. Ilić. In 2010 Remco worked closely together with Dutch DSO Enexis to assess the impact of electric vehicles charging on their distribution networks. Later he worked as a visiting PhD student at the Massachusetts Institute of Technology in 2011 and at Carnegie Mellon University in 2012, where he mainly focused on the role of EVs in small-scale renewable energy systems. During his PhD research, Remco enjoyed being involved in education by supervising master students and giving several guest lectures on EVs and smart grids in BSc, MSc and post-graduate courses. He initiated the Power Rangers, a group of researchers on electricity related topics coming together in informal weekly meetings. Remco's ambition is to continue working in the scientific fields around the economics and operation of power systems, with a special focus on renewable energy sources.

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