Managing Flexible Loads in Residential Areas

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Abstract

Policy makers foster the use of clean, renewable electricity generators. These mainly decentralized, small units with intermittent output are in conflict with the current power grid control infrastructure. Demand response, the active participation of the demand side, is a promising option for efficient and reliable operation of future power systems. Today, demand response programs focus mainly on large industrial customers. Yet, the large number of households should also be tapped into demand response, particularly, since highly flexible loads in residential areas are expected to increase (e.g., electric vehicles or stationary batteries). Consequently, demand response potentials need to be addressed and appropriate mechanisms to coordinate a large number of small flexible units need to leverage. This work concentrates initially on building appropriate models for demand response analysis and elaborates an accurate representation of customer reactions in smart grids. The model is then used to evaluate potentials of two distinct demand response scenarios—direct load control and price-based incentives.

Under direct load control an aggregator can combine flexible loads and intermittent renewable energy sources into one portfolio to increase load coverage with renewable generation. A large amount of flexible customers in a portfolio is not necessarily sufficient to balance load and generation. It turns out that for demand scheduling electric vehicles and storage heaters are the most promising devices and on the supply side an equally balanced wind and photovoltaic mix leads to the lowest procurement costs for the aggregator. Furthermore, direct load control models facilitate the determination of key properties for load flexibility. The analysis suggests that load balancing potentials are mainly influenced by electricity consumption and shifting distance of a device. Scheduling restrictions have limited effect.

Owing to the highly distributed nature of residential loads, appropriate coordination mechanisms are of great importance. While price-based incentive schemes seem to be a straight-forward approach, their applicability has recently been seen more pessimistic as they may induce new load peaks in systems with large shares of flexible loads. The demand and supply model serves to evaluate two desynchronization approaches for price-based load control—power-based surcharges and group pricing. In principle, using power-based surcharges is an effective means, but entails some limitations for real-world applications. Group pricing can achieve promising results with respect to load synchronization and overall system efficiency while providing a simple and reliable price signal to the customers.

This work contributes to the energy informatics literature by providing a detailed model for demand response analysis to gain insights with respect to the key properties of load flexibility and novel coordination mechanisms for small, distributed loads.

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Chapter 1

Introduction

Greenhouse gas emission targets and the goal to increase independence of fuel imports are main drivers for today's energy policy decisions. On the international level, a large number of countries harmonized to reduce greenhouse gas emissions. The European Union and particularly Germany formulated especially ambitious reduction goals: In Germany, greenhouse gas emissions shall decrease by at least 80 % in 2050 as compared to the 1990 level (BMWi and BMU, 2010). To this end, renewable energy sources (e.g., wind turbines or photovoltaic panels) are a key factor. In the sectors with the largest shares of primary energy consumption, electricity and transportation, policy makers put forward the utilization of renewable sources. Utilities hence face a fundamental structural change.

In the electricity sector the goal is to increase renewable generation as a share of total consumption from today 25.3 % to 80 % in 2050 (BMWi, 2014b). An increasing number of decentralized and intermittent Renewable Energy Sources (RES) conflicts with the current control infrastructure. The existing power grid is designed to distribute electricity from large, centralized and constantly generating power plants. The supply-demand balance is maintained via storage facilities and dispatchable power plants. In a system with a high share of renewable generation adequate reserves for balancing power require high investments in more flexible generation or major storage capacities. Another, less capital intensive, approach is to allow for an active participation of the demand side (Strbac, 2008).

In the transportation sector the electrification of individual mobility is a crucial part of the strategy to reduce greenhouse gas emissions. Thus, many countries promote the use of electric vehicles (IEA, 2013). At the end of 2013 there were 17,094 electric vehicles active in Germany (BMWi, 2014b). To comply with the emission reduction targets 6m electric vehicles shall be put on the road by 2030 (Federal Government of Germany, 2011). The potential of Electric Vehicles (EVs) to reduce emissions can only be tapped if charging energy is covered by renewable generation. Interestingly, the trends in electric power generation and transportation are interrelated as charging of EVs will interlink these two historically separated sectors. Increasing loads due to charging will pose additional challenges to the power system. However, as EVs park most of the time, charging loads are highly shiftable and thus promising candidates for coordination.

Demand response, the active participation of the demand side, provides an interesting option to achieve more efficient power system operation. Customers in a Demand Response (DR) program adapt their electricity usage through direct load control or price-based incentives (Albadi and El-Saadany, 2008). This flexibility allows to adjust electricity consumption in accordance with renewable generation and supports their integration into the power system. Realizing DR programs requires Information and Communication Technology (ICT) and thus establishes a smart grid. This vision for the future power system facilitates data exchange and active management of demand and distribution grid components (e.g., substations). In addition to physical grid and ICT infrastructure, the smart grid includes also software and control systems and allows to create business models on top of the technical system (Blumsack and Fernandez, 2012).

Today, DR service providers such as Entelios leverage flexibility of large individual industrial or commercial customers. In contrast, residential areas have small individual loads. Given the increasing shares of decentralized renewable generation, aggregating a large number of small customers to tap their flexibility offers also potentials for system balancing (Goebel et al., 2014). Particularly, the adaption of highly flexible loads, such as EVs or stationary batteries, is expected to increase. This raises questions concerning DR potentials and appropriate mechanisms to coordinate a large number of small flexible units in residential areas. Furthermore, appropriate evaluation techniques are required.

1.1 Evaluating Demand Response Effects

Field trials and living labs are important methods for system experiments. They provide real-world data on the acceptance and effects of new concepts facilitated through a smart grid infrastructure. The MeRegio project is one example for the contributions of field tests. In this project, about 1,000 residential customers received time varying electricity prices allowing to analyze the willingness to participate in DR measures and changes in consumption behavior (EnBW, 2012). However, real-world experiments are expensive, and only a small number of technologies or control strategies can be evaluated to keep costs within a reasonable limit.

Smart grids facilitate a large number of new concepts for power system operation or customer services. For a comprehensive analysis a model representation of the system can be leveraged to study the effects of different alternatives. Using modeling techniques, reliable experimental results can only be achieved if the relevant characteristics for the decision to be made are adequately reflected (Law, 2011). In their smart grid research agenda Ramchurn et al. (2012) emphasize that a model-based analysis of DR effects requires an accurate representation of customer reaction and power system.

Demand modeling in electricity systems can be performed with different techniques. In the literature bottom-up models are often applied to represent DR behavior. By using typical technical characteristics and usage patterns they allow for detailed and realistic modeling of individual devices. Further, emerging technologies, such as EVs or stationary batteries, can be integrated to assess their impact on the system. Yet, highly detailed models are not always desirable as they increase computational complexity and hence may impede large scale simulations. To this end, a balance between model details and performance has to be struck. This trade-off becomes even more important when including a representation of the power system. Therefore, some studies focus on the generation side. They make use of simple demand models and employ real-world plant characteristics to create an operation schedule. Stylized supply models in the way of Grünewald et al. (2015) can reduce complexity and input data requirements for supply modeling.

1.2 Scope

Given adequate modeling techniques to analyze DR effects, the question of how to implement the individual components remains. Therefore, one focus of this study is to provide an approach for demand and supply modeling which is used to evaluate DR potentials and coordination mechanisms. For the demand side, after a discussion of important model properties, an implementation of bottom-up models for devices in a residential area is presented. Individual models are provided for household appliances with temporal flexibility in their operation. Furthermore, emerging technologies (e.g., EVs and stationary batteries) with increasing penetration in residential areas and considerable load flexibility are included. On the supply side a stylized generation model represents a power system with a large share of intermittent volatile renewable generation and includes variable generation costs of dispatchable conventional generation.

The demand and supply models are then used to quantify the system benefits an aggregator can harness by combining flexible loads and volatile renewable generators. This corresponds to the concept of a Virtual Power Plant (VPP) where various small actors come together buying and selling electricity as one cluster. The aggregator can directly control flexible loads in the cluster to increase coverage of loads by renewable generation. A large amount of flexible customers in the portfolio of an aggregator is not necessarily enough to balance load and generation (Petersen et al., 2013). This motivates the first research question:

Research Question 1 – Portfolio Composition. *What is the impact of demand and supply side composition on load balancing?*

Flexibility in electricity consumption enables an active participation of the demand side. The Oxford English Dictionary Online (2014) defines flexibility as “[the] capacity for ready adaption to various purposes or conditions”. This description emphasizes *capacity to adapt* and *purpose* as the two dimensions of flexibility. In this study load flexibility serves to adapt electricity consumption to the generation output from volatile RES (purpose). The balancing potential of individual devices (capacity to adapt) helps to identify the most promising candidates and can guide efforts for DR programs. To facilitate such an analysis, the influence factors for load flexibility have to be identified and quantified. Thus, the second research question is:

Research Question 2 – Flexibility Characteristics. *What are key features characterizing demand flexibility?*

Assuming full information, aggregators applying direct load control will be able to determine optimal (i.e., minimal costs or emission) schedules for flexible loads. Yet, standard drawbacks of centralized regimes apply, e.g., security concerns or computational complexity of large-scale optimization. To mitigate these problems alternative coordination mechanisms need to be considered.

Price-based load control is another promising approach for the design of DR programs (Borenstein et al., 2002). However, recent research has been pessimistic with the applicability of price signals due to the tendency of creating load peaks (Sioshansi, 2012). This part of the study revisits the price-coordination conundrum for standard rate designs and introduces additional elements to address the following research question:

Research Question 3 – Load Desynchronization. *How and to what extent can herding effects of flexible loads be avoided under price-based incentives?*

Reducing the over-coordination of flexible loads can help to improve power system costs. Yet, in a system with a large share of renewable generation a price-based DR program should incentivize shifting of flexible loads according to RES output. For this, adaptive retail prices dynamically reflecting grid conditions can in theory achieve almost optimal results. However, increasing complexity impedes a real-world application of adaptive prices for retail customers. Dütschke and Paetz (2013) point out that customer acceptance of DR programs will require simple and reliable price signals. To facilitate the integration of even higher renewable generation levels, solutions moderating the disparity between customer acceptance and system needs are of great interest. This motivates the final research question:

Research Question 4 – Load Coordination. *Which coordination mechanisms are appropriate to balance between customer preferences and system requirements?*

1.3 Major Contributions

The main contribution of this thesis to the research field of energy informatics are shortly described in the following. An adequate representation of demand behavior and power system is important for model based DR analysis. To this end, a literature review provides insights in the trade-off between complexity and adequacy of existing models. This overview serves as a basis to establish bottom-up models for demand flexibility of household appliances, stationary batteries and EV charging. For each model a detailed discussion of demand response characteristics and a formalized consumption model is provided. On the supply side a stylized power system model with a large share of renewable generation and conventional generation is applied.

One focus is the evaluation of synergies a demand aggregator can achieve through direct control of flexible loads to balance volatile renewable generation. A simulation based analysis indicates that benefits of DR emerge beyond renewable generation shares covering 50 % of total load. For the demand side of the aggregator's portfolio the thesis at hand indicates that in a residential area stationary batteries, EVs and storage heaters are the most promising devices. On the supply side an equally balanced wind and Photovoltaic (PV) portfolio leads to the lowest procurement costs for the aggregator. Furthermore, direct load control in residential areas allows to derive key properties of load flexibility. The evaluations suggest that the capacity to adapt and thus the potential for load balancing is mainly influenced by electricity consumption and shifting distance of a device. The restrictions for scheduling are of less importance.

Coordination of a large number of flexible loads is a key issue for residential DR. Due to herding effects recent publications have been more skeptical with the applicability of price signals for realizing DR. This thesis revisits price-based coordination and demonstrates that standard rates are appropriate for coordination in systems with small shares of flexible loads. In systems with large flexibility they lead to load synchronization and deteriorate efficiency. This motivates the introduction of power-based surcharges and group tariffs. While for power-based surcharges some restrictions for real-world application apply, group tariffs show promising results with respect to load synchronization and overall system efficiency. The evaluations suggest that under uncertainty in renewable generation group pricing is a robust coordination mechanism which can exploit a large share of DR potentials. Furthermore, group pricing does not give rise to fairness issues as benefits of customers increase with their flexibility resolving the cross-subsidies of current flat tariffs. Hence, the results suggest that in the short and medium term, regulators faced with the integration of high levels of RES should try to promote dynamic yet reliable price signals in form of group pricing.

1.4 Structure

To present the modeling approach and to carry out the analysis of the research questions outlined, the work is structured as follows: Chapter 2 provides an overview of the central functions of the electric power system. Further, the smart grid vision for future power system management is sketched and DR benefits and program designs are discussed.

Chapter 3 describes the simulation framework for the analysis of DR. Initially, the relevance of modeling for system analysis is discussed and an overview of the power system functions included in the simulation is given. Subsequently, the bottom-up models for demand flexibility of household appliances, stationary batteries and EV charging are introduced. For each model a discussion of basic characteristics, input data for calibration and a formalized consumption model is provided. Finally, this chapter analyzes output characteristics of renewable generation and presents the stylized power system model.

Chapter 4 focuses on the synergies an aggregator achieves by combining various residential consumers and intermittent generation units in a portfolio. Applying direct load control, a central entity can schedule flexible loads to make use of zero marginal cost renewable generation. After a short overview of centralized optimization approaches in power system analysis, the model formulation and possible applications are presented. Further, the evaluation scenario is described, and one example week serves to illustrate the effects of direct load control. Then, the model is applied to investigate the impact of varying demand and supply side composition on the aggregator's balancing potentials. To this end, flexible loads in the portfolio are scheduled based on day-ahead forecasts of wind and PV generation.

Residential households can expect some form of incentive payments for the provision of load flexibility to the aggregator (Albadi and El-Saadany, 2008). In the second part of this chapter, the value of individual devices for DR is estimated and serves to identify customers that can benefit from participating in such programs. The value of individual devices for DR also serves to determine key features characterizing load flexibility and to prioritize flexible loads for DR applications.

Chapter 5 investigates coordination mechanisms for a large number of small flexible loads. The focus is on price-based control. First, a model for price-based load control and the basic evaluation settings are described. Assuming a power system with a large share of flexible loads (high EV penetration), an example driven style is used to analyze key factors causing herding under different standard rate designs, e.g., Real-Time Pricing (RT). Then, rate design options to reduce load synchronization are explored. The stylized generation model is applied for a comprehensive assessment of different coordination mechanisms.

In this analysis randomized group pricing can be identified as a promising coordination approach. To get insights for a greater number of real-world power systems, randomized group pricing is evaluated in a more comprehensive scenario including a wider set of flexible loads and intermittent generation sources. Furthermore, the impact of uncertainty in renewable generation under price-based control is investigated. A main focus of this evaluation is the comparison of centralized and decentralized coordination under uncertainty. Furthermore, the expected electricity bill savings of residential households and fairness issues of price-based coordination are discussed.

Chapter 6 summarizes the main findings and provides conclusions from the evaluations. Finally, further aspects of analysis and a short outlook on future research topics are addressed.

Some parts of this thesis have been previously published or are the basis for working papers. The respective publications are referred in the introductory paragraphs and as a footnote at the corresponding position within each chapter.

Chapter 2

Electric Power System

A reliable and affordable electricity supply is one important prerequisite for economic growth and employment. The existing power system successfully achieved these goals by generating electricity in large and dispatchable plants and using high voltage transmission lines to supply low voltage distribution grids where end consumers are connected. In the last decade sustainability of electricity supply gained in importance. Hence, the share of small and intermittent renewable energy sources steadily increased posing new challenges to retain high reliability and low costs levels.

This chapter describes the central functions of the electric power system to create a basic understanding of relevant system components and operational principles (Section 2.1). These fundamentals of the current system allow to better assess the impacts of ongoing transformations and arising challenges and help to put the research presented into a system context. Further, in Section 2.2 the concept and potentials of smart grids—a promising approach to manage ongoing changes and address arising challenges in the power system—are illustrated. Finally, Section 2.3 discusses the key transformations against the background of this thesis.

This chapter is partly based on own publications. The paragraphs in Section 2.2.3 on centralized and decentralized control are part of the working paper of Flath and Gottwalt (2014). In the same section the discussion on characteristics of the commodity electricity has previously been published in our joint work (Flath et al., 2013).

2.1 Fundamentals & Transformations

The power system incorporates all functions for generation, transmission and distribution of electrical energy to meet the load requirements of customers. In comparison to other goods, electricity has some unique properties. The major difference is that electric power can not be stored cost-efficiently (Stoft, 2002), and supply has to match demand all the time. For this reason, the power system functions are highly dependent on each other. In the following, system structure and the current operation paradigm are presented. Further, the different functions in the power system are discussed in more detail.

2.1.1 Structure & Operation Paradigm

The value chain in the power system is given by generation, transmission and distribution, and consumption. Figure 2.1 provides an overview of the current power grid structure in Germany based on the functions of the value chain. The figure uses the four voltage levels for transmission and distribution and lists generation and consumption components typically assigned to these levels. The extra high voltage grid serves to connect large dispatchable conventional generation units (e.g., coal, gas or nuclear power plants) or large renewable energy sources (e.g., offshore wind power) and to transport their generation to areas with large consumption. On the high voltage distribution level dispatchable conventional generators and renewable energy sources (e.g., wind onshore or large PV plants) of medium size are connected. On the consumption side electricity intensive industries and cities are supplied. The medium voltage distribution grid connects on the customer side small towns and industrial or commercial enterprises and on the generation side small conventional and renewable generators. Low voltage distribution serves residential households and small commercial businesses. Generation units on this level comprise small dispatchable decentralized plants, e.g., Combined Heat and Power Plants (CHPs) or small renewable energy sources, e.g., rooftop PV systems. Transformers are applied to transfer electricity between voltage levels.

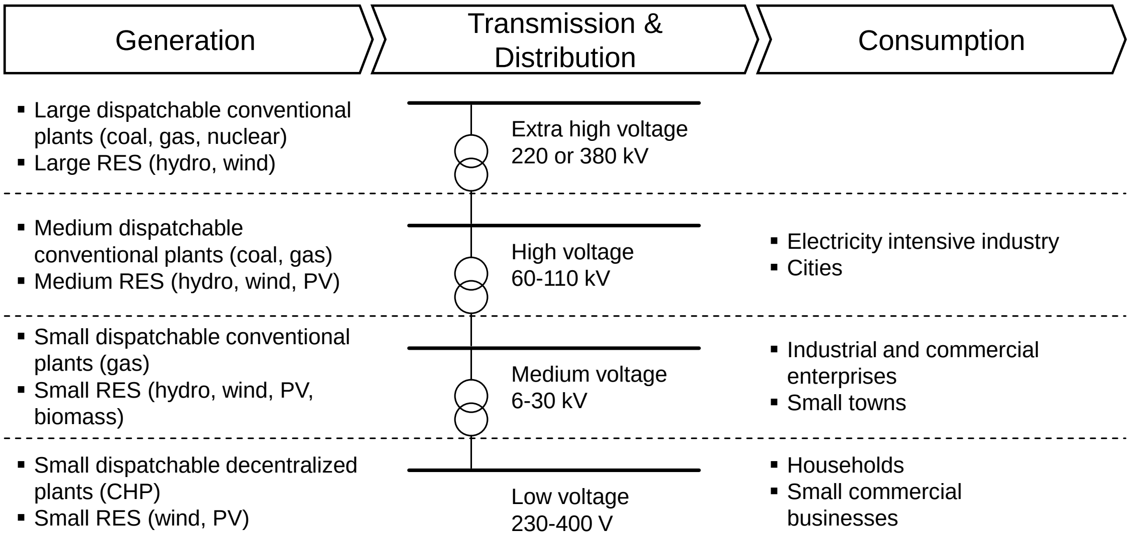

Figure 2.1: Functions of the power system and components on different voltage levels

To guarantee reliability and stability in the power system, generation has to match consumption at every instance of time. If this critical balance is not accomplished, system stability is at risk and destruction of equipment or power failures can occur. The dominant power system operating paradigm is “supply follows demand”. This means that consumers can always change their load and generators have to adjust their output accordingly. Currently, on a day-ahead basis a mixture of forecasting tools, storage facilities (e.g., pumped-storage hydroelectricity), and large, dispatchable power plants that increase or decrease their output, achieve a balanced schedule. On short-term ancillary service providers absorb deviations by providing balancing power for frequency stability (Stoft, 2002). The interaction of day-ahead schedules and short-term ancillary services allows electricity generation to match demand and balance the system.

2.1.2 Generation

Various technologies with large differences in input, operation characteristics, costs and scalability are available for electricity generation. Given these heterogeneous options, generation portfolios of countries show large discrepancies. Key drivers for portfolio composition are costs of technologies and availability of fuel or renewable energy sources to reduce import dependencies. For example, Norway has large potentials for renewable generation and supplies 99.7 % of its electricity consumption by hydro stations.[1] In contrast, France decided in the 1970s to reduce dependency from fuel imports and promoted the construction of nuclear plants. Today, more than 75 % of the country's electricity is supplied by this power source. The world's largest electricity consumer, China, has to supply a rapidly growing economy. To enable a stable and affordable electricity supply in such a dynamic environment China installed and still is constructing ample coal generation capacities. In 2012 more than 75 % of electricity production originated from coal. In comparison, Germany has a more diverse generation portfolio where electricity is mainly generated from coal (45.6 %), nuclear (15.8 %), gas (12.3 %) and different renewable energy sources (23 %). A more comprehensive overview of the electricity generation per source and the installed capacities in Germany is given in Figure 2.2. Despite the heterogeneous fuel shares, one common characteristic among the generation portfolios of countries can be identified. Historically large generation units have been installed to achieve economies of scale and reduce costs in power generation (Stoft, 2002).

In the past, in Germany, but in a similar fashion also in other countries of the Organization for Economic Co-operation and Development (OECD), a state-owned regulated monopolist integrated all functions along the value chain of the power system. After the liberalization of the electricity market started (in Europe triggered by the European Parliament and Council of the European Union, 1996) free market access for all participants on generation and consumption side has been allowed. The generation portfolios with large conventional units required major investments due to size and long economic life time of the plants. Hence, restructuring of the German electricity sector resulted in an establishment of four big generation companies (RWE, E.ON, Vattenfall, EnBW). Despite the increase of renewable energy sources, these four companies are still possessing a dominant position and account for about 73 % of total installed capacities (BNetzA, 2014).

For an operational schedule of the generation system plants are used in order of increasing marginal costs of generation (Schweppe et al., 1988). This merit order

[1] Generation shares per country in this paragraph are based on data of the International Energy Agency (IEA, 2014).

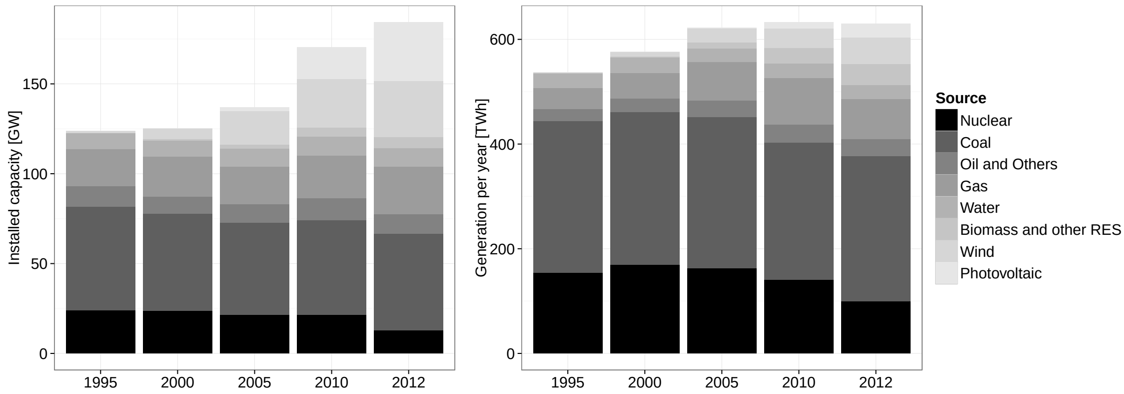

Figure 2.2: Development of installed capacity and electricity generation per year for different energy sources in Germany (Data source: BMWi, 2014a)

dispatch is shown in the left panel of Figure 2.3. The balance between demand and supply is achieved by scheduling generation capacity to meet the forecasted electricity demand. In addition to generation dispatch, the merit order curve determines the market price of electricity at the intersection of demand and supply.[2] The merit order approach ensures that demand is served by the available generators with the lowest costs. Clearly, this leads to different utilization levels of plants. Nuclear and coal power plants can be classified as base load generation. With low variable generation costs they are often scheduled, and there are limited incentives for ramping up and down. In contrast, so-called peaking plants (e.g., gas) have higher generation costs and operate only at peak consumption hours. Thus, they frequently vary their output level and achieve rather low utilization.

In the German electricity generation portfolio a large structural change is ongoing as importance of renewable energy sources is constantly growing. The left panel of Figure 2.2 depicts this development over the last almost 20 years. Starting in 1995 with installed wind and PV generation of 1.1 GW in a system with a total generation capacity of 124 GW this value increased to 63.9 GW at the end of 2012 in a system with 184.4 GW generation capacity (BMWi, 2014a). In future, increasing renewable generation capacities can be expected to comply with the renewable generation targets of the federal government. In a power system with such large shares of renewable sources the economics of existing conventional generation plants

[2]This section only gives a general idea of generation dispatching. For a more detailed description of the electricity market in Germany see, for example, Ockenfels et al. (2008).

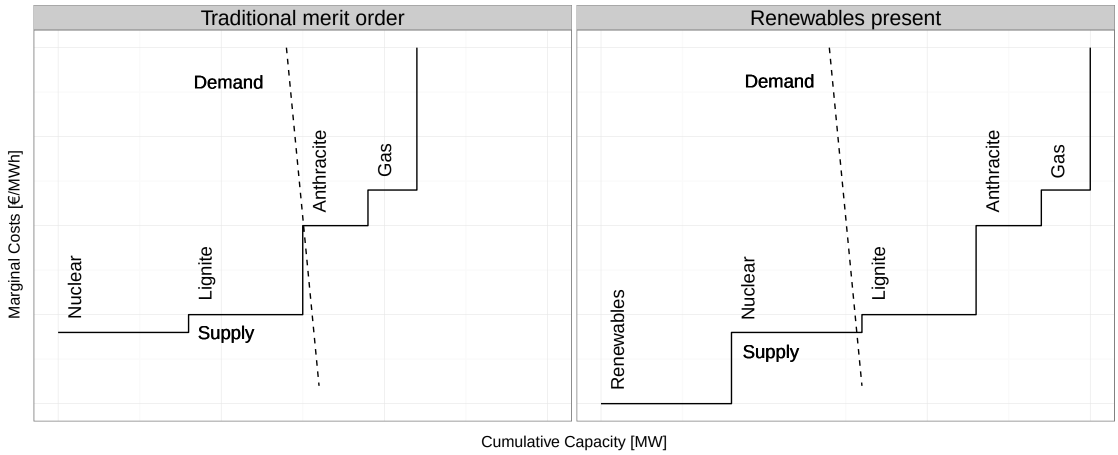

Figure 2.3: Traditional merit order curve of electricity generation and the impact of renewable energy sources (Figure adapted from Flath, 2013b)

are affected. The supply from low marginal cost renewable generators shifts the merit order curve to the right and reduces electricity wholesale prices. This merit order effect of renewable energy sources is described by Sensfuss et al. (2008) and is illustrated in the right panel of Figure 2.3. Hence, lower wholesale prices reduce the revenues of conventional generation plants. Simultaneously, renewable energy sources more often replace conventional plants and reduce their utilization levels.

Installed generation capacities of renewable energy sources increase to a much larger extent as their share on total generation per year (see Figure 2.2). Given the stochastic generation profile for wind and PV, low availability levels often emerge and can explain the delta between capacity and generation shares. Balancing in such a system with a large amount of volatile renewable generation requires a technological mix of base- and peak-load plants. Particularly, more flexible ramping capacity is required to cope with rapid changes in renewable generation output. Yet, decreasing wholesale market prices and utilization levels largely reduce the attractiveness of flexible power plants and impede investments in new capacities (Traber and Kemfert, 2011). Discussions on measures to foster investments in fast ramping capacities include, for example, a more integrated market design remunerating capacity provision and energy supply (Vries, 2007).

2.1.3 Transmission & Distribution

Locational decisions of large and centralized power plants have been influenced by availability of fuel and cooling water, accessibility or risk factors. The extra high voltage level serves to transport generation of these plants to areas with large consumption. The three voltage levels of the distribution grid supply customers of different size and link smaller conventional and renewable generations units to the system. Figure 2.1 depicts the different voltage levels and the connected consumers and generators. Electricity grids require high investment in infrastructure similar to other network industries and are seen as natural monopolies (Filippini, 1998). Despite the liberalization process in the power system, transmission and distribution remain a regulated sector. In Germany firms act as Transmission System Operators (TSOs) or Distribution System Operators (DSOs) for certain areas under a government-granted monopoly. In their area system operators are responsible for stability and reliability. Therefore, their main tasks are management, maintenance and expansion of the power grid. Further, TSOs provide ancillary services for the interconnected transmission system including, for example, frequency or voltage control (Schwab, 2012). The companies Tennet TSO, 50Hertz Transmission, Amprion and TransnetBW are the four TSOs in Germany. Altogether they are responsible for almost 35,000 km of extra high voltage lines. More than 800 companies act as distribution grid operators supervising 1.7 million km of power circuits and supplying more than 48 million end customers. Table 2.1 summarizes some basic numbers to give an impression of the power system size in Germany.

System operators have to incorporate high security margins when designing the system to cope with unusual worst case events. On transmission and high voltage distribution levels N-1 redundancy ensures high robustness. In such a system crucial components have at least one backup, and the failure of one asset (e.g., line, transformer or generator) does not threaten overall system stability. Costs of transmission and distribution grids are typically allocated to end customers according to their total consumption (e.g., Germany) or the selected power rating (e.g., France).

The high shares of renewable energy sources pose significant challenges to transmission and distribution grid infrastructure. Increasing generation on distribution

Table 2.1: Data on power grid structure in Germany (Source: BNetzA, 2014)

	TSO	DSO
Number of companies	4	806
Total circuit length [km]	43,841	1,753,290
Circuit length per voltage level		
Extra high (220/380 kV)	34,780	490
High (60-110 kV)	61	95,364
Medium (6-30 kV)	0	507,953
Low (230-400 V)	0	1,149,973
Total number of customers	649	48,769,032
Number of customers per sector		
Industry & commercial	509	3,046,244
Residential households	140	45,722,788

grid level might invert traditional power flow from high to low voltage grid levels. Therefore, DSOs have to invest in new grid capacities or apply more intelligent management options in future. For Germany the total volume of required distribution grid investments is estimated by more than 25 billion euro until 2030 (dena, 2012). Despite the decentralized generation of renewable sources, investments in transmission capacities are needed to couple new areas with large generation and consumption centers. In Germany, large on- and offshore wind farms emerge in the northern part and have to be connected to the industrial centers in the south. According to the four TSOs, investments of more than 20 billion euro are required during the next ten years (Feix et al., 2014).

2.1.4 Consumption

In Germany electricity accounts for about 21 % of total final energy consumption and thus ranks third after crude oil and natural gas (AGEB, 2014). Figure 2.4 shows the share of different sectors on electricity consumption. It can be observed that total electricity consumption was continuously increasing but started to decline after 2010 approximating today the 2005 level. The largest consumption shares can be allotted to the sectors industry and residential households.

For an appropriate procurement of electricity utilities estimate demand by applying standardized load profiles for small customers (households, agriculture, etc.). Large industry customers with yearly consumption exceeding 100,000 kWh are equipped with measurement technology, and load curves in 15-minute resolution are retrieved. Utilities can improve electricity procurement by estimating future energy demands based on these historical time series. Traditionally, demand is largely unresponsive due to missing incentive schemes and the lack of enabling technologies. Today, only large commercial and industrial customers face demand charges based on their maximum load level giving some stimulus to reduce peak consumption. Another example for flexible loads is given in the German household sector where a ripple control signal is applied to desynchronize operation of storage heaters.

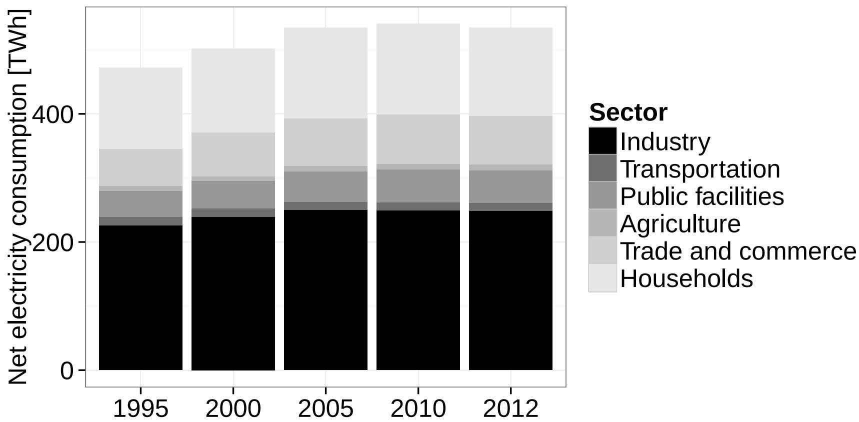

Figure 2.4: Development of total final electricity consumption per sector in Germany (Data source: BDEW, 2014)

Efforts to promote smart grids have put forward both development of technical solutions to enable an active demand side as well as concepts to manage flexible loads. These developments pave the way to overcome the supply follows demand paradigm and enable an active and more efficient contribution of demand *and* generation to system stability (Strbac, 2008). Industrial customers exhibit large load flexibility potentials, and aggregators such as Entelios[3] or Comverge[4] offer already today demand response services to exploit them. Load flexibility potentials in residential household consumption often lie idle. Given the increasing shares of renewable sources and

[3]`http://entelios.de/industrie/`
[4]`http://www.comverge.com/home/demand-response/`

the associated need for adaptive generation or demand, future grid control procedures should also tap flexible loads of smaller customers. Moreover, load flexibility in residential areas can be expected to increase with higher penetrations of EVs or stationary batteries.

2.2 Smart Grid

The ongoing changes towards a supply based on renewable generation units call for adaptions in the traditional operation schemes of the power system to retain high reliability and low cost levels in future. To this end, today's "blind" and manual operation along with the electromechanical components have to be transformed into a smart grid (Ipakchi and Albuyeh, 2009). The European Union (EU) definition of smart grids emphasizes the overall goals for a reliable and affordable electricity supply EU Commission Task Force for Smart Grids (2010):

> "*A smart grid is an electricity network that can cost efficiently integrate the behavior and actions of all users connected to it—generators, consumers and those that do both—in order to ensure economically efficient, sustainable power system with low losses and high levels of quality and security of supply and safety. [...] A smart grid employs innovative products and services together with intelligent monitoring, control, communication, and self-healing technologies [...].*"

The vision of the smart grid requires a fundamental re-engineering of the current system. This technical dimension is highlighted by the U.S. Department of Energy (2003):

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

Realizing a smart grid requires infrastructure enhancements. Power system components have to be equipped with sensors and controllers to monitor and alter operation conditions. Furthermore, modern information and communication technologies are needed to enable data exchange and handling. The potentials of a smart grid infrastructure can only be exploited by appropriate software to manage the vast amount of data. Moreover, applications integrating the heterogeneous components to improve system control and to offer new services to customers are required (Varaiya et al., 2011). Particularly distribution grids, where at present hardly any status information or control options exist, will be heavily affected by this transformation.

In the following, a short overview of currently discussed key components and concepts of a future smart grid is provided. Then, DR is discussed in more detail and potential benefits for the system and design options for DR programs are presented. DR and Demand Side Management (DSM) are used as synonyms within this thesis.[5]

2.2.1 Challenges

A smart grid allows for an active integration of various small and distributed actors into the operation of the power system. This vision for power system operation gives rise to new challenges for algorithms and mechanisms that can deal with a large number of these very heterogeneous actors. Furthermore, they must be able to operate in an environment with significant levels of uncertainty and dynamism and guarantee reliability and security of the control and communication infrastructure (Ramchurn et al., 2012; Goebel et al., 2014). One of the major advances of a smart grid is the possible transition from the supply following load paradigm into a system with both sides playing an active role. Multiple ideas to organize actors and improve power system operation are currently under discussion. A common characteristic among all ideas is flexibility in generation and, even more important, in consumption of electricity. Based on components and concepts of Ramchurn et al. (2012) a brief overview of this discussion is presented in the following:

[5] DSM sometimes describes a portfolio of measures to improve the energy system at the consumption side (Palensky and Dietrich, 2011). Yet, more recent smart grid publications use the term DSM to describe mechanisms for redistribution of loads.

Electric Vehicles EVs are important to reduce carbon emissions in transportation. Their high energy needs place a considerable amount of additional load to the power system and require sophisticated coordination mechanisms to distribute their charging activity. Yet, long parking times result in a high temporal flexibility of charging loads which can make EVs a key resource in a smart grid.

Virtual power plants To cope with the large number of actors in a smart grid they can be bundled to expose synergies between them. Generators and consumers can come together forming an virtual power plant with the objective to sell or buy electricity as an aggregate.

Energy prosumers On individual household level the widespread adoption of renewable energy sources and building automation systems will lead to prosumers (households producing and consuming electricity). Those households can be part of virtual power plants or act directly on electricity or flexibility markets.

Self-healing networks More detailed information on grid level and the availability of prosumers or virtual power plants pave the way for active management techniques on distribution grid level and allow to build self-healing mechanisms, e.g., voltage correction via transformers or controlled EV charging.

Demand Response The active coordination of flexible loads can offer sizable control potential and help to improve power system efficiency by flattening peak loads or integrating renewable energy sources. As DR is also in the focus of this thesis, DR benefits and design of programs for its implementation are presented in more detail in the remainder of this section.

2.2.2 Benefits of Demand Response

Demand response can improve power system efficiency along all functions of the value chain (Strbac, 2008). On the generation side DR can reduce security requirements of generation capacity and facilitate demand and supply balancing with volatile RES. For transmission and distribution grids DR improves investments and operation efficiency. Customers require appropriate incentives to participate in DR programs

(Blumsack and Fernandez, 2012). Thus, utilities have to—at least partially—pass welfare gains due to increasing efficiency to their customers.

The fundamental functions generation, transmission, distribution and consumption serve to structure the discussion of DR benefits identified by existing scientific publications. In accordance with the focus of this thesis, the overview emphasizes DR for demand and supply balancing in residential areas. As DR is a highly popular topic and affects different research communities, only selected publications are presented.

Generation

Various researchers engage in the estimation of supply side effects of residential DR by either looking at peak shaving or demand and supply balancing. Lower peaks lead to less fluctuations in consumption. Hence, they reduce the required system generation capacity and result in a higher utilization of existing plants. The work of Ramchurn et al. (2011), Kishore and Snyder (2010) and Costanzo et al. (2011) analyze peak shaving potentials of residential DR under different control regimes. Reduced load peaks influence also supply based emissions. Changes in base load and peaking plants utilization result in a modified fuel mix and emission level (Sioshansi, 2012). The effect (increase or decrease) in emissions depends on the scheduled generation units.

A growing branch of research is looking into demand and supply balancing via flexible loads in a system with volatile renewable sources (Aghaei and Alizadeh, 2013). The basic effect of DR in such a system is depicted in Figure 2.5. In the absence of renewable energy sources, generation costs and scheduled capacity are given at the intersection of demand (D) and supply (S) marked by point A. Availability of renewable sources gives rise to the previously described merit order effect and thus a shift of the supply curve (S') decreases marginal generation costs (B). Yet, a flat pricing regime does not provide incentives for consumers to adapt electricity demand and despite lower costs demand remains at a constant level. DR allows for adaption in consumption and facilitates a more efficient electricity generation. Under

DR electricity demand is elastic[6] (D'), and in a power system with a large share of renewable generation electricity consumption can be shifted according to the availability of their output level. In times with low renewable generation (S) demand can be reduced avoiding utilization of high cost capacities ($A \rightarrow A'$). In contrast, when a large amount of renewable generation is available (S') demand increases making use of low cost electricity ($B \rightarrow B'$).

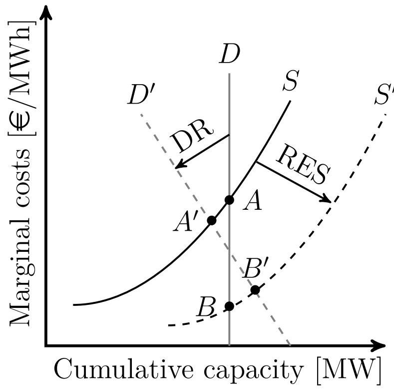

Figure 2.5: Effect of renewable generation (RES) and demand response (DR) on dispatched capacity and marginal costs of electricity

Among others, Vandael et al. (2011), Lopes et al. (2009) or Subramanian et al. (2012) try to assess effects of flexible loads to balance demand and supply in the presence of a large renewable generation shares. In different settings they investigate real-time scheduling of EV charging loads and analyze remaining load imbalances. Tushar et al. (2014) model and control operation of home appliances and charging of EVs to maximize the use of local renewable generation. Their objective is to reduce imported electricity in a microgrid.

Transmission

For a TSO flexible demand can serve to provide ancillary services. Due to the large temporal flexibility in charging and their large loads, EVs are a promising device for such a service. Hence, various researchers investigate the potential of EVs for regulating power (Andersson et al., 2010; Sortomme and El-Sharkawi, 2012; Vandael

[6]See Kirschen et al. (2000) for an in-depth treatise on the concept of demand elasticity applied to the commodity electricity.

et al., 2013). Stadler et al. (2009) focus on the provision of short term balancing power by residential cooling devices.

Distribution

One main area of research covers the assessment of demand flexibility potentials in distribution grids. Among others, Clement-Nyns et al. (2011) and Lopes et al. (2009) show how EVs can support a distribution grid in terms of voltage control and congestion management. Reductions of peak load and losses in the power system are addressed, for example, by Sortomme et al. (2011) and Acha et al. (2010).

Consumption

Customers participating in DR programs can expect incentive payments or lower electricity bills due to reduced consumption in peak periods (Jazayeri et al., 2005). Yet, the economic viability of DSM for residential households is limited (Gottwalt et al., 2011). They might also benefit from system wide effects like an overall electricity price reduction, better reliability in supply or improved market performance (Albadi and El-Saadany, 2008).

2.2.3 Design of Demand Response Programs

Various options exist to implement DR programs for customers. Albadi and El-Saadany (2008) provide a basic categorization and distinguish between incentive- and price-based regimes. Under classical incentive-based programs customers receive more favorable contract conditions (e.g., a bill credit or lower base fee) and cede load control to the system operator or an intermediary, such as an energy retailer or demand response aggregator. This corresponds to a setting of *centralized load control*. Price-based programs emphasize a *decentralized decision* paradigm by applying dynamic pricing to incentivize changes of customer behavior (Borenstein et al., 2002).[7] Subsequently, these two decision paradigms are presented in more detail.

Centralized Control

In centralized control schemes a designated entity, typically referred to as “aggregator” or “load controller”, schedules the operation of flexible loads (Subramanian et al., 2013). Assuming full information, such a central operator will be able to determine an optimal (i.e., minimal costs or emissions) dispatch schedule for the loads. At the same time, standard drawbacks of centralized regimes apply, e.g., security and privacy concerns, computational complexity of large-scale optimization or incentive compatibility problems may arise. To mitigate some of these problems, several authors propose hierarchical schemes where load subgroups are controlled by a local aggregator, e.g., on the distribution grid level (Callaway and Hiskens, 2011).

Decentralized Control

In contrast, decentralized control regimes show lower computation and communication requirements. Furthermore, they maintain customer incentives and respect privacy concerns (Vandael et al., 2011). The implementation of price-based DR will require some form of dynamic pricing, e.g., Time-Of-Use (TOU) pricing, Critical Peak Pricing (CPP), or RT pricing. The seminal work addressing electricity pricing and demand response is due to Schweppe et al. (1988). They present a framework to establish an energy market place and propose that electricity should be treated as a commodity taking into account its time- and space-varying values and costs. Efficiency gains in the electricity system along these two dimensions have been demonstrated for time-based (Newsham and Bowker, 2010) and spatial pricing schemes (Dupont et al., 2014).

The temporal component of electricity pricing reflects the market price of generation. The merit order schedules power plants according to their marginal costs

[7] The introductory text and the paragraph on centralized control in this subsection are currently part of our working paper Flath and Gottwalt (2014). The discussion on decentralized control combines parts of our papers Flath and Gottwalt (2014) and Flath et al. (2013).

of production. As renewable energy sources have almost zero variable costs, they displace expensive peaking plants. Thus, availability of renewable generation results in a lower market clearing price.

Cost of transmission and distribution grids are the drivers behind spatial price differences. Considering all operational constrains of the system leads to nodal pricing. Under this regime each point where electricity is generated or consumed has a distinct price (Bohn et al., 1984; Eßer-Frey, 2012). This large number of nodal prices might be too complex for end customers. An alternative which reduces this complexity is given by zonal pricing. Here, the price within one area of the grid changes according to the local system state.

2.3 Development Path

The traditional power system with large and dispatchable centralized power stations, long transmission lines and a distribution system for power delivery to static end consumers is currently evolving to a new approach (Ipakchi and Albuyeh, 2009). The main driver behind this transformation is the aim to reduce greenhouse gas emissions and the political promotion of renewable energy sources. Their decentralized and volatile generation conflicts with the current power grid control paradigm and requires a rethinking of system management. The smart grid vision with technologies to monitor and alter system conditions and new applications for improved operation will play a crucial role in the future. A smart grid helps to overcome the load following paradigm and allows for an active participation of the demand side. One key factor is the understanding of complexities and the emergent behavior of a smart grid incorporating a large number of small and distributed agents to guarantee high reliability of electricity supply. In the same line, this thesis puts the demand side in the center and investigates potentials and coordination mechanisms of flexible loads in residential areas.

Chapter 3

Smart Grid Modeling

Following the previous part on power system basics and transformations, this chapter provides a simulation framework for the analysis of flexible loads in a future smart grid. On the demand side representative models for the flexibility in electricity consumption of household appliances, stationary batteries and EV charging are developed. These models allow to generate realistic consumption profiles and to represent DR behavior. On the supply side a stylized generation model is presented to evaluate effects of flexible loads in the power system. The simulation framework is used to analyze DR effects in the remainder of the thesis.

Section 3.1 discusses different ways to study a system and the relevance of modeling for system analysis. Further, an overview of the power system functions included in the simulation framework is given. In Section 3.2 existing approaches for modeling electricity consumption of residential populations are reviewed. After that, using a bottom-up approach models for demand flexibility of household appliances, stationary batteries and EV charging are introduced (Sections 3.3 to 3.5). For each flexible load type a discussion of basic characteristics, the applied input data to calibrate the model and a formalized consumption model are given. For the supply side a short overview of existing models is presented in Section 3.6. Section 3.7 complements the supply side description by an analysis of renewable generation output characteristics and by the introduction of the stylized power system model.

The material in this chapter was partially discussed in own publications:

- Some parts of Section 3.3.1 and 3.3.2 origin in Gottwalt et al. (2011).
- Input data in Section 3.5.1 and the simple model in 3.5.3 for EV charging are based on the joint work of Flath et al. (2013).
- The stylized power system in Section 3.7.2 is part of a working paper which has been submitted for publication (Flath and Gottwalt, 2014).

3.1 Power System Analysis

There are two general ways to study a system, either by performing experiments with the actual system or by experiments with a model of the system. Both ways lead to a better understanding of the dependencies between system components and the behavior of the system under new conditions. Evaluating system changes by extending the system physically is the most desirable way, as "there is no question if the study is valid" (Law, 2011). Such real-world system extensions are often costly, and hence system models are a more viable alternative for analysis. Challenges related to the introduction of DR are investigated via real-world system tests and modeling. Both ways to study a system are discussed in the following. Then, an overview of the components included in the simulation framework to study residential DR is given.

3.1.1 System Experiments

DR experiments with the actual system are mainly employed in form of field trials and living labs. In field trials limited aspects of a new technology or a service can be tested in a real-life environment (Ballon et al., 2005). An example for such a field trial in Germany provides the research project MeRegio[1] where about 1,000 residential customers received dynamic tariffs. Within this project the willingness to participate in DR measures and the changes in electricity consumption due to

[1] http://www.meregio.de/

dynamic tariffs have been evaluated. Furthermore, about 250 residential households have been equipped with controllable fridges to investigate DR potentials for the integration of decentralized energy sources (EnBW, 2012). Field tests provide important real-world data on the effects of introducing DR programs (e.g., customer acceptance or technological viability), but they can incorporate only a small number of new technologies and control strategies at the same time to keep costs within reasonable limits.

Living labs are a human-centric method for creation and validation of new ICT solutions. In a real-life experimentation environment the needs of users and the interests of other relevant stakeholders can be integrated right at the start of the innovation process (Bergvall-Kareborn et al., 2009). In Europe user-centric research with living labs or similar concepts has recently become popular (Eriksson et al., 2005). Two examples for living labs focusing on DR research are the Energy Smart Home Lab at the KIT Karlsruhe Institute of Technology[2] and the House of Living Labs at the FZI Research Center for Information Technology[3]. Both labs represent a small apartment and are equipped with smart appliances for (automated) load control, an EV, a PV system, a CHP with a thermal storage and a human-machine interface (Becker et al., 2012). In the Energy Smart Home Lab test residents experience DR technologies and load control regimes during experimental living phases of several weeks or months. In these living periods the behavior of the residents and their acceptance of different elements of DR programs can be evaluated (Paetz et al., 2013). The apartment at the House of Living Labs serves as a platform to integrate interests of users and relevant stakeholders to realize DR services, e.g., component manufacturers (Becker, 2014). At the same time, both living labs provide a test bed for concepts to integrate heterogeneous communication protocols of various devices into one system and show the technological viability of a smart home (Allerding et al., 2010). In general, living labs allow to integrate users in the innovation process for an appropriate design of products and services and enable to show the feasibility of a broad range of new technologies and control strategies for DR. Due to high costs for living labs only a very small number of customers can be evaluated in the real-life environment and overall power system effects cannot be analyzed.

[2]http://meregiomobil.forschung.kit.edu
[3]http://www.fzi.de/forschung/fzi-house-of-living-labs/

3.1.2 System Modeling

Field trials and living labs make major contributions in the development of innovative and user-friendly DR solutions. However, high costs limit the number of scenarios that can be investigated. To analyze more comprehensive settings, a simulation model as a representation of the system can be built and used to study system wide effects (Hirsch et al., 2010). Yet, simulation experiments are artificial as they are based on computer models (Harrison et al., 2007). For reliable experimental results it is important that the model adequately reflects the relevant system characteristics for the decisions to be made (Law, 2011). Furthermore, the model's input parameters should be grounded on empirical data. This way, a simulation can be a valuable research tool to explore the consequences of new concepts in a smart grid and guide costly research activities with the real-system.

In the smart grid research agenda of Ramchurn et al. (2012) a representation of demand behavior and power system is identified as relevant for model based DR analysis. Thus, models for electricity consumption and generation have been formulated and implemented in this thesis. Limitations in transmission and distribution grids are neglected, due to three practical reasons: Firstly, an integrated grid model drastically increases computational time of a population model. Secondly, data for realistic grid modeling is difficult to obtain. Finally, distribution grids are very heterogeneous. This assumption is in line with most recent non-engineering smart grid publications investigating DR potentials of customer populations (Shinwari et al., 2012; Tushar et al., 2014). However, grid constraints pose important restrictions to guarantee a reliable power supply (Ipakchi and Albuyeh, 2009), e.g., with increasing EV charging demand overloads in the distribution grid might occur more frequently. Pecas Lopes et al. (2009) show in a simple setting how demand and supply balancing can be integrated into a power grid model. For future work, Nolden et al. (2013) give different options how distribution or transmission network constraints can be considered in techno-economic power system models. Figure 3.1 shows the basic functions of the power system and confines the components on demand and supply side implemented.

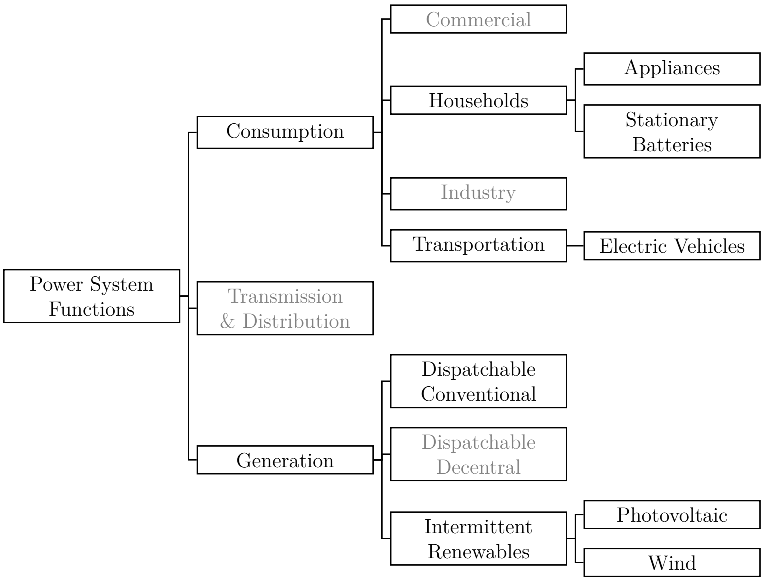

Figure 3.1: Basic functions of the power system and components implemented in the simulation framework

On the consumption side DR potentials are available in all sectors. Due to their high overall loads, customers in the sectors industry and commercial exhibit significant load flexibility. These potentials are already tapped today by demand aggregators. At the same time, individual customers in these sectors largely differ in total consumption and flexibility characteristics (Winter, 2014). For a simulation based study heterogeneity in consumption units requires detailed modeling on individual level impeding an efficient analysis on larger scale. Currently residential households show only limited economic viability for DR (Gottwalt et al., 2011). However, future system operation should also account for additional flexibility resources so far untapped. Here, the sectors household and transportation can provide interesting options. Particularly, the increasing share of EVs results in large additional electricity consumption in residential areas.

For an impact analysis of DR, an adequate representation of the power system is required. As noted before, on the supply side various electricity generation options are in use. The focus of this work is to evaluate DR potentials for the integration of intermittent renewable sources. Thus, the supply side comprises PV and wind generation units. Flexible loads should ideally be scheduled to maximize utilization from intermittent sources. In other terms, residual load which needs to be covered through additional conventional generation should be minimized. In line with existing research on DR a stylized power system model is applied to represent conventional generation (Sioshansi, 2012; Grünewald et al., 2015). For the sake of simplicity, small and decentralized dispatchable sources (e.g., combined heat and power plants) are not included in the model. Supply aggregators (e.g., Lichtblick[4]) tap potentials to control such distributed units already today. Models for demand (residential appliances, stationary batteries and EVs) and supply side (dispatchable conventional generation) are presented in more detail in the remainder of this section.

3.2 Scope of Demand Models

Creating a model with characteristics as close as possible to real-world leads to reliable results on emergent system behavior and can improve settings for field trials and living labs. Residential demand in a smart grid is formed of various small actors. Specifying these actors on micro level with a high degree of detail increases computational complexity. This problem especially has to be addressed for an analysis of system effects where a large number of actors has to be considered.

To balance between model complexity and adequacy, Flath (2013b) proposes a framework to structure the modeling process of smart grid customers using model size and scope, static customer and demand response characteristics and model adaptivity over time (see Figure 3.2). Along this structure the residential demand models are elaborated in the following. In this section, a discussion of basic demand modeling techniques is provided and the size and scope of existing DR investigations is mapped to the customer model characteristics giving insights in the trade-off between complexity and adequacy. After that, the static load and demand response characteristics of the models for household appliances, stationary batteries and electric vehicles are presented. Model adaptivity over time, the forth step of the modeling process, is out of scope.

[4] `http://www.lichtblick.de/geschaeftskunden/schwarm-energie/schwarm-produkte/zuhausekraftwerke/`

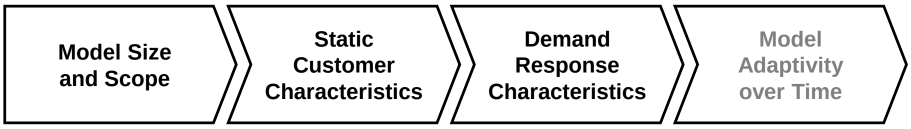

Figure 3.2: Structured customer modeling (based on Flath, 2013b)

3.2.1 Techniques for Demand Modeling

Two categories of modeling techniques for residential household electricity consumption can be identified in literature: top-down and bottom-up approaches. In the following these two approaches are shortly described. A more detailed discussion of top-down and bottom-up models and also various examples of existing models are presented by Swan and Ugursal (2009) or Grandjean et al. (2012).

Top-down approaches consider energy consumption of a sector as a whole and trace consumption back to characteristics of the sector. Commonly used variables for these models are economic indicators, weather conditions or estimations of device ownership. Based on projections for these variables long-term changes in energy needs are estimated and can guide the planning of grid resources (e.g., supply requirements). Due to their simplicity, scalability and the widely available aggregated data, top-down models will continue to play an important role for system analysis. They can be applied, for example, to forecast future supply requirements with increasing energy efficiency in residential household appliances. Top-down models can also be used for high-level analysis of future technologies, e.g., penetration rates of photovoltaic systems. However, they lack in estimating potential impacts of new technologies on system level (Swan and Ugursal, 2009). Furthermore, top-down models analyze a sector as a whole and are therefore less applicable for smaller customer populations in a decentralized power system.

Bottom-up models use data on a level below the entire sector and create load profiles on device or household level and then project these results to represent a region. Existing bottom-up approaches largely vary in their level of detail and input data. Input data often includes consumption and technical characteristics of appliances, climate properties or human behavior, but can also encompass a broad range of other variables. Bottom-up approaches facilitate a residential demand model with a high level of detail. Hence, such models permit to evaluate impacts of new technologies, for example, electric vehicles and allow to assess different DR schemes. However, with an increasing level of detail two disadvantages arise with bottom-up models. Firstly, the computational complexity of the model increases and might impede simulations of large appliance or household populations (Griffith et al., 2008). Secondly, statistical input data might not be available in the required resolution and model assumptions become somehow arbitrary.

Overall it can be stated that for the evaluation of demand flexibility bottom-up approaches allow detailed modeling and enable integration of new technologies. In order to reduce complexity and data input requirements, it might be reasonable to abstract from some real-world characteristics. Here, existing bottom-up models can provide some guidance.

3.2.2 Models for Residential Demand Response

Several research publications focus on bottom-up models for residential electricity demand. They identify important characteristics for realistic artificial load profiles. Walker and Pokoski (1985) present one of the first residential load models. They integrate residential behavior to the components connected to the power system at a particular time and create realistic load profiles for two homes in the United States. Capasso et al. (1994) base their detailed behavioral model of the household residents on data from a time use survey.[5] Furthermore, they use available data on appliances, e.g., penetration levels or power demand, to create appliance profiles for households. Then, they summarize the household load curves to estimate load in an Italian residential area. Similar bottom-up approaches are provided by Widén and Wäckelgård (2010) and Richardson et al. (2010). These models also use time use and appliance data as inputs and generate load patterns for domestic electricity demand in Sweden, respective the United Kingdom. Some of these models discuss DR as a possible application, however, none is applied to evaluate such effects. Nevertheless, these comprehensive models establish presence of residents and consumption statistics to

[5] A time use survey measures the amount of time people spend during various activities, e.g., preparing meals, laundry or watching TV.

describe residential behavior and properties of individual appliances as important characteristics for detailed bottom-up residential load models.

More recently, different aspects of residential DR have been investigated by electrical engineers and energy economists. Driven by the individual research objectives, the applied bottom-up models in these investigations vary largely in their level of detail and the required input data. Without claiming to be complete, Table 3.1 provides an overview of existing models created for residential DR assessment. The table includes main properties of the detailed bottom-up models complemented by thermal needs and the number of flexible appliances and possible future devices for residential DR (static customer characteristics). Combining these features with the model size (population, horizon and DR devices) and scope (coordination approach and objective), the table allows to identify important characteristics and motivate reasonable assumptions for reducing model complexity.

The table illustrates that researchers investigating single residential households tend to apply more detailed models with various flexible appliances, future devices and amplified use of statistical input data. Furthermore, evaluations for single household models are typically executed for simulation horizons above one month. In addition, DR models evaluating large populations with one million or more households can be identified. Here, researchers use very simple models, a small number of appliances and simulate only short periods. Similar to this thesis, most publications investigate a local or regional population between 50 and 5,000 households. To handle complexity these models even out between simulation horizon, the number of flexible appliances, and the input data applied. The work at hand incorporates a large set of flexible devices for a residential area and simulates a rather long period (12 weeks). For model calibration the standard input data is considered.

Table 3.1: Overview on residential demand response models in literature

Type	Reference	Coordination approach and objective	Scenario		DR devices		Input data			
			Household population	Simulation horizon	Flexible appliances	Future technologies	Presence	Consumption statistics	Appliance properties	Thermal needs
Single household	Allerding (2014)	Home energy management for appliances and local generators via evolutionary algorithm to increase self-consumption or reduce electricity bill.	1	1 yr.	7	CHP	✓	✓	✓	✓
	Scott et al. (2013)	Control of residential loads under dynamic pricing and uncertainty in prices, weather and occupant behavior. Use of online stochastic algorithms to assess electricity bill savings.	1	1 mo.	6	BAT EV	✓	✓	✓	✓
Local population	Gottwalt et al. (2011)	Generation and validation of residential load profiles. Application of dynamic pricing to shift appliance operations estimating electricity bill reductions and effects on peak load.	1,000	1 yr.	7		✓	✓	✓	
	Huang et al. (2011)	Micro level household model which can be applied to study policies affecting appliance set. Economic evaluation of PHEV charging competitiveness under different pricing schemes.	US-CA	1 day	0	PHEV		✓	✓	
	Kamper (2010)	Fridges, freezers and CHP plants are grouped in a pool and build a peer-to-peer network. Neighbors exchange information to reach a balanced load schedule in the pool.	1,001	1 day	2	CHP		✓	✓	
	Kishore and Snyder (2010)	Distributed scheduling mechanism for dishwasher, dryer and water heater to reduce peak demand of residential homes.	50	5 days	3				✓	

Table 3.1: Overview on residential demand response models in literature

Type	Reference	Coordination approach and objective	Scenario		DR devices		Input data			
			Household population	Simulation horizon	Flexible appliances	Future technologies	Presence	Consumption statistics	Appliance properties	Thermal needs
Local population	Ramchurn et al. (2011)	Decentralized DR mechanism based on variable electricity prices for dryer, washing machine and thermal load to evaluate effects on peak demand and carbon emissions.	5,000	∼ 3 mo.	3			✓	✓	✓
	Shinwari et al. (2012)	Decentralized control of dryer, washing machine and EVs via starting time probabilities for peak shaving and valley filling.	1,000	1 day	3	EV			✓	
	Stadler et al. (2009)	Direct control and indirect load control of fridge operation to provide short-term balancing power in a region.	5,000	1 day	2			✓	✓	
	Tushar et al. (2014)	Direct control of washing machine, dishwasher, dryer, battery and EVs and decentralized control of EV charging to use local wind and PV generation.	200	1 day	3	EV			✓	
Federal population	Guo et al. (2008)	Self-adaptive approach for load control of air-conditioning to reduce energy consumption while retaining a stable comfort level.	1m	3 days	1				✓	✓
	van den Briel et al. (2013)	Distributed approach for scheduling of washing machine, dishwasher and dryer operation based on probabilities for start times to achieve a given ideal load.	2.5m	1 day	3	EV			✓	

3.3 Household Appliance Model

Existing bottom-up models show how scientists calibrate models to fit their research objectives. Based on their design decisions, distinct properties of residential household load models are discussed and a configuration for such a model is given in the following. Further, demand response characteristics of household appliances and a formalized consumption model are presented.

3.3.1 Static Load Characteristics

In a bottom-up model household appliances are represented individually. As modeling of single appliances requires detailed input data, only appliances suitable for DR are integrated in the simulation framework. The set of flexible appliances represents about 52 % of total residential load. For the remaining share of household electricity consumption, so called base load, industry standard load profiles describing consumption over time are applied. The input data used to calibrate appliances in the load model and the approach to calculate base load are described in more detail subsequently.[6]

Input Data Requirements

To calibrate the appliance models data of different degree of detail is used. Four categories of input data can be identified (see Section 3.2.2): presence of residents, consumption statistics, appliance properties, and thermal needs. Presence of residents is important as it effects usage of various appliances (e.g., lighting or dishwasher). However, integrating presence leads to inter-dependencies of appliance usage on household level and increases model complexity. Models of load populations mainly avoid this complexity and do not include presence. For such models a valid representation of system wide load is important and dependencies of appliance runs on a single household level can be neglected. To derive runtimes of appliance populations often consumption statistics on average appliance usage are applied. By this,

[6] The sources for input parameters to calibrate the household appliance model origin from our paper Gottwalt et al. (2011).

valid load profiles for a population can be generated, but investigations on individual household level are not possible. Appliance properties are used by all publications as input data for load models and include, for example, penetration level, power consumption and operation duration. Thermal requirements of households only need to be considered, if Heating, Ventilation or Air-Conditioning (HVAC) is integrated in the model (Ramchurn et al., 2011; Guo et al., 2008). Most of the existing models do not include HVAC appliances.

Input Data Applied

Following Widén and Wäckelgård (2010), three steps for the determination of load profiles of a household population can be identified. Firstly, the number of appliances within the population has to be calculated. Applying penetration levels of appliances as probability of availability creates a set of appliances for the population. Secondly, the number of operations or runs of an appliance has to be determined by :

$$\frac{\text{Average energy consumption per household} \cdot \text{Consumption share appliance}}{\text{Energy per run} \cdot \text{Appliance penetration level}} \tag{3.1}$$

Yearly electricity consumption of a German household is about 3,100 kWh (BDEW Bundesverband der Energie- und Wasserwirtschaft e.V., 2013), respective daily consumption 8.5 kWh. Data to calculate the number of operations or runs per appliance is shown in Table 3.2. The usage of storage space heating varies between seasons and equals 1 in winter, 0.25 in transition and 0 in summer. Due to lack in data, operation of the remaining appliances does not vary between seasons.

The third step, determining the consumption times of appliance runs is the most critical factor. Storage space heating systems, storage water heaters, fridges and freezers are modeled independent of customer activity (Widén and Wäckelgård, 2010). The first two appliances in this list are usually operated at off-peak periods and distribution grid operators set activation times at night (Stamminger, 2009). For the residential load model without DR it is assumed that staring times are equally distributed between 0 am to 5 am and appliances run in one continuous stretch.

Table 3.2: Input parameters for calibration of the household appliance models

Appliance	Penetration level	Consumption share	Energy per run [kWh]	Cycle duration [min]
Refrigerator	0.997[a]	0.09[b]	0.024[d]	15[c]
Freezer	0.505[a]	0.07[b]	0.035[d]	15[c]
Storage water heater	0.08[d]	0.133[d]	16.0 [c]	240[c]
Space heating	0.04[d]	0.131[d]	32.0[c]	240[c]
Dishwasher	0.673[a]	0.037[b]	1.206[a]	105[a]
Washing machine	0.945[a]	0.036[b]	0.888[a]	105[a]
Dryer	0.391[a]	0.024[b]	2.485[a]	105[a]

Sources: [a]Statistisches Bundesamt (2013), [b]Bürger (2009), [c]Stamminger (2009), [d]Own calculations based on Bürger (2009) and Stamminger (2009)

Fridge and freezer operate frequently to keep temperature in a defined range. In the load model one day is divided into intervals, with one active cycle per interval. For the intervals a length of 45 minutes is assumed. Within the intervals the cycles are equally distributed.

Runs of washing machine, dishwasher and tumble dryer are based on customer activity. To determine starting times for these appliances hourly starting probabilities are applied, which are based on the typical usage of these appliances (Stamminger, 2009). Hourly probability values for the operation starts are shown in Figure 3.3. Reasonably, dryer operation shows a delay of approximately three hours as compared to the washing machine. Note that starting probabilities for all appliances do not vary with day type, as there are no reliable statistics available.

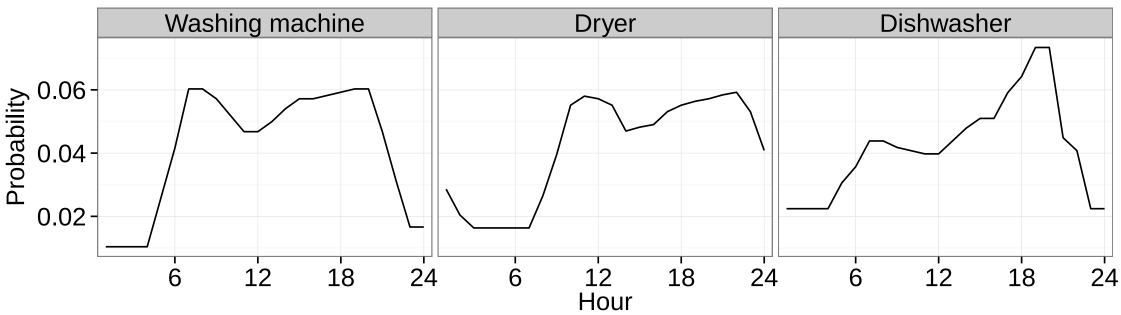

Figure 3.3: Hourly starting probabilities based on typical usage patterns (Data Source: Stamminger, 2009)

For the base load in the household population standard load profiles are applied. The Federal Association of Energy and Water Industries (BDEW) in Germany provides this profile, called H_0, in a 15 minute resolution for the average electricity consumption of a norm German household. To consider the load of the individual modeled appliances values of the standard load profile are scaled to 48 % of their original value. The profile differs between three season (summer, winter, transition time) and three day types (Saturday, Sunday and working day) (Fünfgeld and Tiedemann, 2001). Figure 3.4 depicts the H0 standard load profiles for an average household with a yearly consumption of 3,100 kWh and the base load applied for the static household demand.

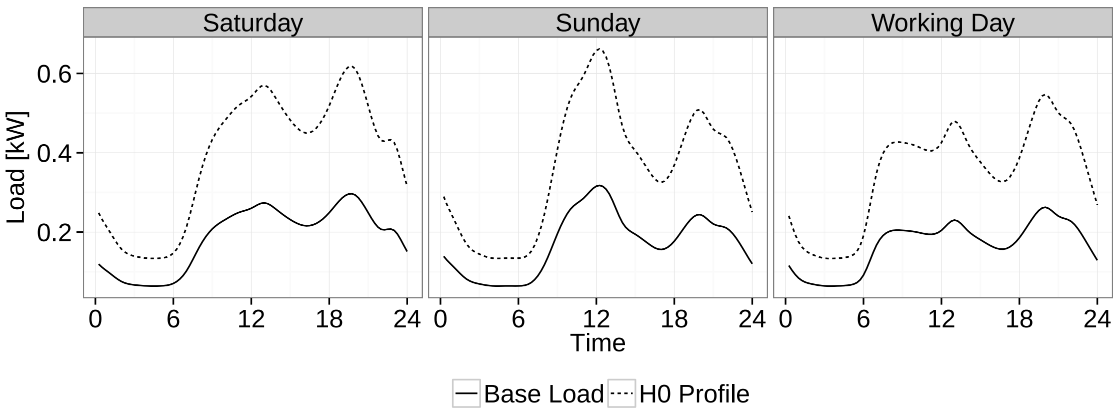

Figure 3.4: Standard load profiles (H0) for average German households and base load for different day types in the transition time (Data Source: http://www.vsg-netz.de/vsgnetz/Stromnetz/Lastprofilverfahren.php)

3.3.2 Demand Response Characteristics

Residential households can be equipped with various different appliances. In a seminal work Schweppe et al. (1989) provide a taxonomy for load flexibility of household appliances and characterize appliances as using "electricity to provide a service to the customer". For DR the usage of electricity has to be changed. Hence, they identify three basic options for realizing DR which are reschedule timing of appliance usage, rescheduling of service and usage to different times, and to reduce service and usage. Table 3.3 shows some examples of household appliances for these options.

Suitability of household appliances for shifting can be evaluated according to the effect (utility or disutility) of DR on customer's convenience. Thus, the effects of DR on the service is used to categorize household appliances in different degrees of automation for operation control. The table indicates suitability of the most relevant household appliances for DR using the characteristics: load during operation, operation frequency, shifting distance, and customer convenience of shifting. Latter is also in use to determine the degree of automation applied for DR. Subsequently, the three control options (automatic, semi-automatic and not-controllable) are described and the effects of DR on the service level of appliances is sketched.[7] A more detailed description of electricity usage and service characteristics of controllable appliances is, for example, presented by Soares et al. (2014).

Table 3.3: Characteristics of household appliances for DR (H-High, M-Moderate and L-Low) and load control in the model. Own elaboration based on the classifications of Schweppe et al. (1989) and Seebach et al. (2009).

Basic DR options	Appliance	Load	Operation frequency	Shifting distance	Customer conven.	Load control in model
Reschedule usage	Fridge	L	H	L	H	Automatic
	Freezer	L	H	L	H	Automatic
	Stor. water heater	H	M	H	H	Automatic
	Stor. space heater	H	M	H	H	Automatic
	Air conditioning	H	M	H	M	None
Reschedule service & usage	Dishwasher	M	L	M	M	Semi-auto
	Washing machine	M	L	M	M	Semi-auto
	Tumble dryer	M	L	M	M	Semi-auto
	Stove & oven	H	M	L	L	None
	Vacuum cleaner	M	L	L	L	None
Reduce service	Lighting	L	M	L	L	None
	Television	L	M	L	L	None

Automatic Control

Appliances that are categorized as automatic control possess a natural thermal storage and do not work continuously. This way, electricity usage and service provision can be decoupled. Customers do not interact with an individual operation of these

[7]This description is an adapted and extended version of our paper Gottwalt et al. (2011).

appliances[8] and within constraints they can be controlled automatically without noticeable differences in utility for household members (Kamper, 2010). Appliances comprised by this category in the DR model are storage water heaters, storage space heaters, refrigerators, and freezers.

On household level both storage heaters are large individual loads, and they are the only appliances in use for residential DR today. Via radio or ripple control distribution grid operators transmit consumption intervals to storage water or storage space heating systems. In these intervals the appliances can turn automatically to refill their storage. Grid operators determine groups of storage appliances and transmit intervals on group level to desynchronize these large loads (Hastings, 1980). Typically, consumption intervals in Germany range from 10 pm to 6 am[9] as these are times with low overall electricity consumption. For future DR the consumption limitation to night hours might not be appropriate, as in a power system with volatile renewable sources consumption should take place in hours of high generation. In the residential DR model presented, it is therefore assumed that storage heating appliances can be activated during the entire day. Furthermore, the refill operation of the storage does not have to take place in a continuous stretch and can be interrupted. With a daily refill of the storage household members will not experience a loss in comfort.

Refrigerator and freezer are appliances with small loads. What makes it interesting to use them for load shifting is their frequent operation and the suitability for automated load control without being noticeable for household members. Refrigerators and freezers cycle frequently to keep the inner temperature in a predefined interval and to prevent food quality of being harmed. In literature the interval to delay or postpone cooling cycles varies from 30 to 60 min (Stadler et al., 2009). In the residential DR model a cooling cycle of refrigerator or freezer lasts for 15 minutes. For load shifting it is assumed, that they have to operate once every 45 minutes for not exceeding the temperature threshold resulting in a maximum idle time of 60 minutes.

[8] Note that consumers might change basic parameters, e.g., target temperature of a fridge.

[9] `https://www.stadtwerke-muenster.de/privatkunden/strom/alle-stromprodukte/nachtspeicher/detailinfos.html`

Semi-Automatic Control

Operation of washing machine, dishwasher, and tumble dryer can be started automatically, but interaction with the consumer is needed before, for example, a dishwasher must be loaded. Due to the required consumer interaction, control for these appliances will be denoted as semi-automatically. To introduce flexibility in the operation of these appliances it is assumed that consumers set appliances into a ready mode (after loading them) and determine the latest feasible finishing time. The operation can then automatically be started within the time constraints defined by the customers. The approach of setting a latest finishing time is in line with existing literature on residential DR (Becker et al., 2012). In this work the loading time is assumed to equal the original starting time derived from the hourly starting probabilities. DR for washing machine, dishwasher and tumble dryer requires rescheduling of service and usage, but as customers can set the latest finishing times their preferences can be considered and it is assumed that the service level is not reduced. In the residential DR model finishing times are randomly selected on an operational basis taking values of 3, 5 or 10 hours.

Not-Controllable

Most household appliances are categorized as not-controllable for the demand model. Some of them might be appropriate for shifting. For example air-conditioners posses a thermal storage to decouple electricity usage and service provision. But, as air-conditioning only has a small share on total electricity consumption in Germany potential for DR is limited and these appliances are not included in the model. However, air-conditioning might offer interesting potentials for residential DR in other countries (Gils, 2014) and for commercial buildings in Germany (Klobasa, 2009).

DR integration of other household appliances decreases customer comfort. For a stove or vacuum cleaner DR participation requires rescheduling of service and usage. Lighting or television can only provide flexibility by reduction of usage and service level. An ICT supported DR for these appliances is not possible. Due to the reduction in customer comfort, they are not included in the model.

3.3.3 Consumption Model

In this work a regional power system which consists of a set of $H \in \mathbb{N}$ households is investigated over a time horizon of $T \in \mathbb{N}$ time slots. Households are indexed $h \in [H]$, where $[H] = \{1, \ldots, H\}$. Time slots are indexed $t \in [T]$. Let M be the set of different home appliances available for the households and, let M^h be the set of home appliances for household h, with $M^h \subseteq M$ for all $h \in [H]$.

In the following, M is split up into three disjoint appliance subsets with similar characteristics in order to generate load profiles for a population of residential households and to analyze DR flexibility of these appliances:

- The first subset $\mathcal{A} \subseteq M$, $\mathcal{A} = \{a_j : j \in [A]\}$, where $A \in \mathbb{N}$ includes automatically controlled appliances with large loads and maximum one run per day. Runs of appliances in this subset can be shifted and interrupted for DR, for example, a single run of a storage water heater.
- The second subset $\mathcal{B} \subseteq M$, $\mathcal{B} = \{b_j : j \in [B]\}$, where $B \in \mathbb{N}$, comprises automatically controlled appliances with small loads and frequent runs during one day. Runs of appliances in subset $\mathcal{B}$ only last for one time slot, for example, a single operation of a refrigerator.
- The latter $\mathcal{C} \subseteq M$, $\mathcal{C} = \{c_j : j \in [C]\}$, where $C \in \mathbb{N}$, consists of semi-automatically controlled appliances operating only few times a week. Runs of appliances in this subset have fixed consumption profiles and cannot be interrupted, for example, usage of a washing machine.

Description Group $\mathcal{A}$

For an automatically controlled appliance $a \in \mathcal{A}$ the simulation horizon T is divided by the number of runs $C_a \in \mathbb{N}$ into intervals of equal length $L_a = \frac{T}{C_a}$. $s_a \in \mathbb{N}^{C_a}$ and $e_a \in \mathbb{N}^{C_a}$ are vectors defining the start and end of a flexibility interval, where $s_a + L_a - 1 = e_a$ and s_a^i and e_a^i are indexing the i-th element of the vector. Each appliance is modeled as a tuple $a = (\rho_a, \delta_a, X_a, C_a, s_a, e_a)$ where $\rho_a \in \mathbb{R}_+$ is the consumption of an active appliance a, $\delta_a \in \mathbb{N}$ is the duration of one run and the vector $X_a = (x_a^1, \ldots, x_a^T)$ with $x_a^t \in \{0,1\}$ describes in which time slots $t \in [T]$ an appliance is active ($x_a^t = 1$) or inactive ($x_a^t = 0$). The duration of a run is defined to be the active time in one interval:

$$\forall i \in [C_a] : \sum_{t=s_a^i}^{e_a^i} x_a^t = \delta_a. \tag{3.2}$$

For DR runs of appliances in group $\mathcal{A}$ can be shifted and interrupted and thus within each flexibility interval the vector X_a has the shape $0^{p_1}1^{r_1}0^{p_2}1^{r_2}0^{p_3}\ldots 1^{r_k}0^{p_{k+1}}$ where $\sum_1^k r_l + \sum_1^{k+1} p_l = L_a$ and $\sum_1^k r_l = \delta_a$. The number of interruptions of one run in an interval is determined by $k-1$. Energy consumption l_a^t by appliance a in time slot t is given by:

$$l_a^t = x_a^t \rho_a. \tag{3.3}$$

Description Group $\mathcal{B}$

For frequently operated appliances $b \in \mathcal{B}$ the simulation horizon T is also divided by the number of runs $C_b \in \mathbb{N}$ into intervals of equal length $L_b = \frac{T}{C_b}$. $s_b \in \mathbb{N}^{C_b}$ and $e_b \in \mathbb{N}^{C_b}$ are the corresponding vectors defining the start and end of an interval, where $s_b + L_b - 1 = e_b$ and s_b^i and e_b^i are indexing the i-th element of the vector. In contrast to group $\mathcal{A}$, the start of the first interval s_b^1 is randomly selected in $[1, L_b]$.[10] The length of the last interval $s_b^{C_b}$ is thus given by $L_b - s_b^1$. A run of appliances in group $\mathcal{B}$ lasts only for one slot. Each appliance is modeled as a tuple $b = (\rho_b, X_b, C_b, s_b, e_b)$ where $\rho_b \in \mathbb{R}_+$ is the consumption of an active appliance b, and the vector $X_b = (x_b^1, \ldots, x_b^T)$ with $x_b^t \in \{0,1\}$ defines activation times of an appliance b. For DR runs of appliances in group $\mathcal{B}$ are flexible within the respective interval $[s_b^i, e_b^i]$ and runs once in every interval:

$$\forall i \in [C_b] : \sum_{t=s_b^i}^{e_b^i} x_b^t = 1. \tag{3.4}$$

[10] This prevents identical intervals for all fridges and avoids load synchronization.

Consumption l_b^t for one appliance b in one time slot t is given by:

$$l_b^t = x_b^t \rho_b. \tag{3.5}$$

Description Group $\mathcal{C}$

For a semi-automatically controlled appliance $c \in \mathcal{C}$ let $R_c = \{r_1, \ldots, r_{N_c}\}$ be the set of runs during the simulation horizon T with $N_c \in \mathbb{N}$. Each run $r \in R_c$ is represented by a tuple $r = (\delta_r, X_r, P_r)$ where $\delta_r \in \mathbb{N}$ is the duration of run r, the vector $X_r = (x_r^1, \ldots, x_r^T)$ with $x_r^t \in \{0, 1\}$ indicates the start of a run ($x_r^t = 1$), and P_r is a vector defining the power consumption profile. A power profile is described by:

$$P_r = (\rho_r^1, \ldots, \rho_r^{\delta_r}), \tag{3.6}$$

where $\rho_r^\tau \in \mathbb{R}_+$ is the power consumption in the τ-th period from start of the operation $1 \leq \tau \leq \delta_r$. It is assumed that each run starts only once during the simulation horizon T:

$$\sum_{t=1}^{T} x_r^t = 1. \tag{3.7}$$

For DR let t_r^s be the time where an appliance is set into a ready mode and t_r^l be the last allowed start time set by household residents. The start of run r has to be scheduled in the flexibility interval $[t_r^s, t_r^l]$:

$$\sum_{t=t_r^s}^{t_r^l} x_r^t = 1. \tag{3.8}$$

The consumption l_r^t of run r in slot t is given by:

$$l_r^t = \sum_{k=1}^{t} \left(x_r^k \cdot P_r \left(t + 1 - k \right) \right) \tag{3.9}$$

where

$$P_r(\tau) = \begin{cases} \rho_r^\tau, & \tau \in \{1, \ldots, \delta_r\} \\ 0, & \text{otherwise.} \end{cases} \tag{3.10}$$

Total Population Consumption

Total consumption of flexible appliances L^t_{FH} for all households in time slot t is given by:

$$L^t_{FH} = \sum_{a \in \mathcal{A}} l^t_a + \sum_{b \in \mathcal{B}} l^t_b + \sum_{c \in \mathcal{C}} \sum_{r \in R_c} l^t_r. \tag{3.11}$$

Let $b^t \in \mathbb{R}_+$ denote the static consumption of all households in time slot t. Then total consumption L^t_{HH} is defined as:

$$L^t_{HH} = L^t_{FH} + b^t. \tag{3.12}$$

3.4 Stationary Battery Model

For a smart grid stationary batteries are interesting components. They offer high flexibility as load control does not affect customer convenience and they are available at all times. Thus, various promising opportunities for electricity storage in stationary batteries can be identified including wholesale energy or power quality services, or their usage for the integration of intermittent renewable sources. In the latter application, stationary batteries allow to decouple generation and consumption as they store electricity in periods with excess generation and provide electricity at low generation periods. Distribution of stationary batteries is currently increasing in residential areas. For practical use, they are principally promoted with the aim to improve self-consumption or autarky rates of a household's PV installation (Müller, 2014). Researchers focus on the performance of storage technologies trying to reduce production costs and to improve durability and efficiency of batteries (Dunn et al., 2011). In addition, they assess potentials of stationary batteries for different applications, e.g., energy arbitrage (Ahlert and van Dinther, 2009; Graves et al., 1999). In the following, basic parameters to configure a stationary battery model are presented and operation strategies to control charging and discharging are discussed. Further, a formalized model is described to integrate stationary batteries into the simulation framework.

3.4.1 Static Load & Demand Response Characteristics

Stationary batteries hold electricity for later use. A load pattern for stationary batteries can only be generated by applying at least a simple rule-based control of charging and discharging based on local generation availability. A separate discussion of static customer and demand response characteristics to derive a customer model can not reasonably be applied for stationary batteries. Thus, in the following the foundation for a stationary battery model is provided by identifying relevant technical parameters and discussing operation strategies for charging and discharging.

Stationary Battery Specification

In literature models for battery storage systems largely differ in the level of technical details applied. Kwan and Maly (1995) provide an example for a detailed technical model incorporating interdependencies of battery parameters. For instance, they include battery voltage fluctuations as a function of the charge state. Ahlert and van Dinther (2009) abstract from these interdependencies and use empirical values as input. The large number of parameters for different parts of the storage system in their model requires an extensive sensitivity analysis for verification. A classic model formulating battery storage scheduling as a linear program is given by Daryanian et al. (1989). Various other researchers apply this model as a basis for optimal scheduling models of flexible loads, e.g., for EV charging (Sioshansi et al., 2010; Flath et al., 2013). Based on Daryanian's model battery storage capacity, and maximum charging and discharging power can be identified as relevant technical parameters to specify stationary batteries. Table 3.4 depicts exemplary configurations of these parameters for stationary battery storage systems currently for sale. For the model in this thesis a virtual battery similar to the BPT-S 5 Hybrid is assumed with 7 kWh capacity and 4 kW charging and discharging power.

Table 3.4: Exemplary configurations of stationary battery storage systems currently for sale (October 2014). Data based on manufacturer information and own calculations.

Model	Battery Capacity [kWh]	Charging Power [kW]	Discharging Power [kW]	Battery type
SENEC.Home G2	8	3	2.5	Lead-oxide (liquid)
E3/DC E4	13.8	4.0	4.0	Lithium-ion
BPT-S 5 Hybrid	6.6	3.75	3.75	Lithium-ion
SunPac 2.0	11.6	2.7	2.7	Lead-acid (gel)
KNUBIX Knut 3.3	5.5	1.6	5.4	Li-iron phosphate
ASD future ON 300	6	1.3	3.5	Li-iron phosphate
Average	8.5	2.7	3.6	

Operation Strategies

Generating load patterns of stationary batteries requires an operation strategy to schedule charging and discharging. For residential households battery system solutions are readily available for sale. These systems often use a simple rule-based control to increase self-consumption of electricity from on-site available renewable sources by charging the battery storage when excess PV generation is available and supplying consumption in later periods.[11] More advanced home automation systems furthermore control operation of household appliances and incorporate battery storage in an integrated energy management for increasing levels of self-consumption or energy autarky.[12]

Scheduling of battery storage based on system wide incentives or direct control to make system services available are mainly addressed in research. Such investigations include for example the exploitation of arbitrage opportunities on spot markets (Ahlert and van Dinther, 2009; van de Ven et al., 2013). Yet, market-ready solutions to schedule battery storage based on system control signals start to emerge. One example is the provision of ancillary services by controlling various small, distributed stationary batteries, thus, also showing the applicability of advanced control

[11] `http://eqoo.ewe.de/#funktionsweise`
[12] `http://www.sma.de/home-systems/solaranlage-smart.html`

strategies for dispersed units.[13] Under a static load regime, i.e., in the absence of incentives or advanced strategies, simple rule-based control schemes could be applied to schedule batteries (Kessler et al., 2015). For instance, to increase utilization of renewable generation a signal might transmit charging or discharging intervals in periods of high or respectively low renewable generation. However, in the work at hand it is assumed that batteries are not in use under a static load regime.

3.4.2 Consumption Model

To integrate stationary batteries in the residential DR simulation framework, a formalized charging schedule model is elaborated, hence, enabling to assess advanced control strategies and exploiting their flexibility to improve power system efficiency. The formulation presented follows the classic linear model for energy storage of Daryanian et al. (1989).

To analyze storage technologies in the residential DR model $S \in \mathbb{N}$ stationary batteries are integrated. In line with the household appliances described, they are investigated over the time horizon T and decisions are discretized using 15-minute intervals. Further, a constant charging power is assumed. The set of stationary batteries is given by $\mathcal{S} = \{s_j : j \in [S]\}$. For one stationary battery s the maximum capacity is denoted by $\overline{b}_s$ and the maximum charging and discharging power by $\overline{\phi}_s$, respectively $\underline{\phi}_s$. Charging or discharging decisions of stationary batteries can be represented as vectors $\Phi_s = (\phi_s^1, \dots, \phi_s^T)$, with $\phi_s^t \in [\underline{\phi}_s, \overline{\phi}_s]$. The battery state-of-charge (SOC) is tracked via the vector $\Psi_s = (\psi_s^1, \dots, \psi_s^T)$, with $\psi_s^t \in [0, 1]$ indicating the share of battery capacity. Thus, each stationary battery can be described by a tuple $s = (\Phi_s, \overline{\phi}_s, \underline{\phi}_s, \Psi_s, \overline{b}_s)$. Charging or discharging of stationary batteries can be scheduled over the course of the simulation horizon:

$$\psi_s^t \overline{b}_s = \psi_s^{t-1} \overline{b}_s + \phi_s^t. \tag{3.13}$$

A value of $\psi_s^0 = 0.3$ is assumed for the initial SOC of stationary batteries. Furthermore, to avoid simulation artifacts and guarantee equal charging and discharging

[13] http://www.senec-ies.com/economic_grid/

amounts over the simulation period initial SOC ψ_s^0 and terminal SOC ψ_s^T are set to the same level:

$$\psi_s^0 = \psi_s^T. \tag{3.14}$$

Total Population Consumption

Consumption or supply for all stationary batteries L_S^t in time t is given by:

$$L_S^t = \sum_{s \in \mathcal{S}} \phi_s^t. \tag{3.15}$$

Another technical aspect in the operation of batteries are losses at various components of a storage system, e.g., rectifier, inverter or storage efficiency. Efficiency for up-to-date storage systems achieves values of more than 90 %. Due to this high efficiency and to reduce model complexity a loss-free charging and discharging with efficiency $\eta_s = 1$ is assumed. This assumption is in line with Daryanian et al. (1989). A detailed discussion of extensions for a more realistic charging model including battery wear is provided with the description of EV charging in Section 3.5.3.

3.5 Electric Vehicle Model

The energy required for the average annual driving distance in Germany[14] roughly equals the electricity consumption of a single person residential household. At the same time, vehicles are driving only short periods of the day and ICT-based systems can schedule charging during long parking hours. Thus, charging loads of electric vehicles are both large and flexible. In addition, the market shares of EVs are expected to increase and their charging activities will heavily effect load and DR potentials of residential areas. Researchers from various disciplines aim to estimate charging loads and evaluate options for charging coordination (Lopes et al., 2009; Sioshansi et al., 2010; Schuller, 2014). Due to the limited availability of EVs, one

[14] Average driving distance per household in 2012 was about 12,700 km per year (Data Source: Statistisches Bundesamt, 2014).

cannot readily obtain data to validate synthetic charging models. Appropriate EV models constitute the base for an integration of charging loads into a residential DR model. In the following, model properties and configuration including demand response characteristics of EVs are given. Moreover, a formalized model for EV charging is elaborated and a discussion on relevance of individual model features is provided.

3.5.1 Static Load Characterization

The overview on existing DR models identifies average usage and properties of devices as key drivers for valid synthetic load profiles. Following literature, e.g., Clement-Nyns et al. (2010), Sioshansi (2012), or Flath et al. (2013) a simple bottom-up EV model to comply with these requirements can be created by evaluating empirical driving profiles using technical EV and charging system specifications. Given the limited availability of EVs, data on real usage cannot be obtained and models are built on empirical driving profiles of conventional vehicles with internal combustion engines. Specifications of EVs (battery size, consumption) and charging system (charging power, efficiency) can be built on real-world systems. Finally, to derive EV charging patterns a charging strategy is needed.[15]

Driving Behavior

Driving profiles for EVs are extracted from the German Mobility Panel (Zumkeller et al., 2010). In this study a representative sample of about 1,000 German households continuously report their mobility behavior during one week of the year. For every trip the mobility data set includes information about the means of transportation, distance traveled, and starting and end time in a 15-minute time resolution. Furthermore, socio-economic data, e.g., household size, gender, age and profession of the household residents is collected. For the simulation all trips made by Internal Combustion Engine (ICE) vehicles are extracted to derive driving profiles and then 1,000 driving profiles from the employee group are selected.

[15] This section is an extended version of the model description in our paper Flath et al. (2013).

For this thesis the panel data is limited to the sociodemographic group of full-time employees. Employees have a large share in the German population and show the highest driving distances (see Table 3.5). Due to the high investment compared to ICE vehicles, EVs can be expected to be used by persons with higher driving needs (Plötz et al., 2013). Furthermore, due to the regular patterns EVs can be ideally used for trips to work. The German Mobility Panel also includes information about the purpose of each trip, i.e, if someone is on the way back home. Out of these trip purposes charging locations for EVs can be derived.

Table 3.5: Driving distances for different professions (Source: Schuller, 2014)

	25 % Quan.	Median [km/week]	Mean	75 % Quan.	Share in Population
Employees	84.0	184.6	225.1	322.2	0.32
Part-Time Employees	48.8	97.5	120.9	158.5	0.11
Retired	61.4	121.3	159.2	209.5	0.34
Unemployed	34.0	77.2	113.8	144.2	0.10

EV Specification

For a model of EV charging both electricity consumption and battery capacity are relevant characteristics. The former, allows to calculate electricity consumption due to driving. The latter, is crucial for the flexibility of charging. In combination they determine the maximum range of an EV. Table 3.6 depicts specifications of EVs currently for sale. For the model the average values of these EVs are applied and a 30 kWh battery and a consumption of 0.15 kWh/km are assumed.[16] This corresponds to a maximum range of 200 km.

Low energy density of batteries limits the range of EVs and causes "range anxiety". A larger battery increases driving range, but also curb weight and electricity consumption per km (Flath, 2013b). Along with high battery costs low energy density is the main hurdle for the large-scale adaption of EVs. Currently most car

[16] Car manufacturers apply the New European Driving Cycle to assess consumption of electric vehicles. Peripherals, such as cooling or heating, are not in included in this test procedure and increase consumption of EVs.

Table 3.6: Technical data of current EVs for sale (September 2014)

Model	Curb Weight [kg]	Battery Capacity [kWh]	Electricity Consumption [kWh/km]	Range [km]	Battery type
BMW i3	1,195	18.8	0.129	145	Li-ion
BYD e6	2,380	61.4	0.217	300	Iron phospahte
Mitsubishi i-MiEV	1,185	16	0.135	150	Li-ion
Nissan Leaf	1,520	24	0.150	160	Li-ion
Renault Kangoo Z.E.	1,410	22	0.129	170	Li-ion
Renault Zoe	1,503	22	0.146	150	Li-ion
Tesla Model S	2,100	60	0.180	335	Li-ion
VW e-Golf	1,585	24.2	0.127	160	Li-ion
VW e-up!	1,214	18.7	0.117	140	Li-ion
Average	1,566	29.7	0.148	190	

manufacturers apply lithium-ion batteries for EVs (see Table 3.6). Energy density of next generation lithium ion batteries is expected to largely increase and overcome "range anxiety" (Pollet et al., 2012). In medium term only lithium-ion batteries are expected to best fit requirements on specific energy, cycle life and costs. However, other alternatives might attain lower costs in the long run (Gerssen-Gondelach and Faaij, 2012).

Charging system

The International Electrotechnical Commission (IEC) standard 61851-1 specifies a set of modes for EV charging. Based on theses modes IEC standard 62196 defines plugs, sockets and cables for charging of EVs. A short overview of the four different charging modes is given in Table 3.7. As the focus within this thesis is on the analysis of residential DR potentials, a maximum charging power of 11 kW corresponding to the connection power of a typical German household is assumed. This results in a duration of about 165 minutes for a full charge of a battery with 30 kWh capacity.

Various researchers investigate potentials of Vehicle-to-Grid (V2G) concepts where EVs are capable of feeding electricity back (Kempton and Tomić, 2005; Lund

Table 3.7: Charging modes specified in IEC 61851-1

Charging mode	Phases	Max. current	Max. voltage	Max. power
Mode 1 (AC)	1	16 A	230 V	3.7 kW
	3	16 A	230 V	11 kW
Mode 2 (AC)	1	32 A	230 V	7.4 kW
	3	32 A	230 V	22 kW
Mode 3 (AC)	3	63 A	400 V	44 kW
Mode 4 (DC)	-	400 A	1,000 V	400 kW

and Kempton, 2008; Mültin, 2014). Providing V2G services to the power grid might decrease lifetime of the vehicle battery. Due to the crucial role of battery costs for a large-scale EV roll-out V2G is not considered in this theses. However, advances in battery technology or increasing revenues for flexibility in the power system can make V2G an interesting option. Then, the proposed model can easily be extended to incorporate V2G (see Schuller et al., 2014).

Simple Charging Strategy

A central decision for evaluating aggregate load and power system effects of EV charging is how to model charging decisions of individual vehicles. Under a static load regime, i.e., in the absence of incentives, it is assumed that EV owners maximize a vehicle's range at any given time. Thus, EVs charge whenever possible choosing the maximum power available. This As Fast As Possible Charging Strategy (AFAP) approach is the simplest strategy as it does not require additional information, such as future trips or electricity prices.

3.5.2 Demand Response Characteristics

A large scale EV roll-out will drastically influence DR potentials of residential households. Compared to the shiftable household appliances discussed before EVs have a high electricity consumption, are very flexible as they are idle over 95 % of a day, and have large storage capabilities (Kempton and Letendre, 1997). For a basic estimation of flexibility in EV charging empirical German mobility data are applied.

A detailed description of the empirical mobility data is provided in Section 3.5.1. Figure 3.5 depicts boxplots for the parking and charging durations at three typical locations for parking of EVs. It is assumed that EVs charge between trips to the full battery capacity using the maximum power (simple charging). The individual charge requests of EVs are expressed in hours while applying a fixed charging power of 11 kWh. Thus, enabling the comparison of charging and parking duration. One can clearly see that charging to a full battery between trips takes usually less than half an hour and can be preformed at all locations. For parking long idle times can be observed at the work and especially the home location offering large flexibility potentials to schedule charging. Thus, in the following it is assumed that charging is possible at the locations home and work.

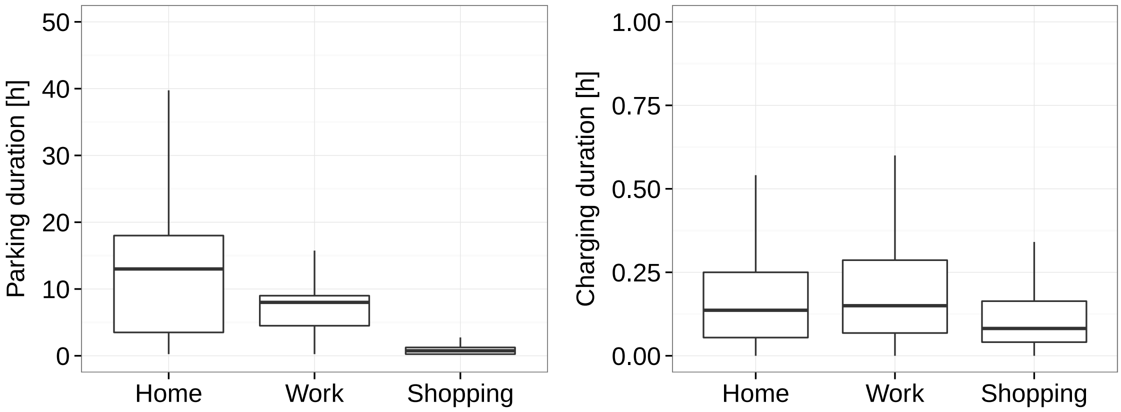

Figure 3.5: Parking and charging duration for different locations

Furthermore, with large storage capabilities of EVs it can be argued that (fully) charging a battery between trips is not always required. Figure 3.6 depicts the cumulative distribution for the maximum number of trips and days a fully charged battery lasts.[17] Obviously, a large share of EVs does not have to be charged on a daily basis. EVs offer also inter-day flexibility as few charging times over the course of a week are sufficient to cover driving needs. As the simple charging strategy is completely static and cannot be influenced by external signals (e.g., dynamic electricity rate, congestion or renewable generation signals), flexibility in EV charging

[17]For the preparation of the figure the starting day of the weekly driving profiles is randomly selected.

cannot be employed. Alternative charging strategies can largely improve on this base-line approach with respect to power system efficiency and charging costs.

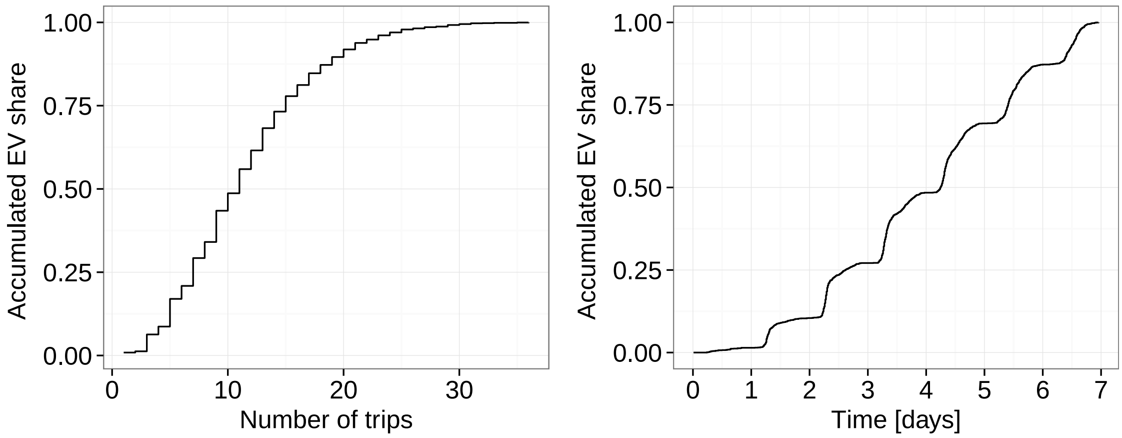

Figure 3.6: Accumulated EV shares for number of trips and days till charging has to take place.

3.5.3 Consumption Model

To integrate EV loads in the simulation framework, a notion of EV charging is presented. This notion allows to formalize the simple charging strategy (AFAP) and builds the basis to evaluate smart charging strategies for EVs by exploiting their flexibility potentials for DR. The consumption model for EVs is an extended version of the battery storage model, as they additionally require a consumption vector based on trips and locational information. However, in this study electric vehicles are not able to feed electricity back to the grid and their charging vector can take on only positive values. The presented formulation is in line with existing work on EV charging, e.g., Sioshansi et al. (2010) and Schuller et al. (2014).[18] The formalized model is complemented by a discussion of user interests, battery wear, and technical characteristics of the charging process as possible model extensions to accomplish more realistic charging behavior.

[18] The formal EV model and the charging strategies in this subsection are adapted from our paper Flath et al. (2013).

Electric Vehicle Model

To analyze effects of future consumption technologies a fleet with $V \in \mathbb{N}$ electric vehicles is integrated into the residential DR model and investigated over the time horizon T. The set of EVs is given by $\mathcal{V} = \{v_j : j \in [V]\}$. To match the temporal resolution of the residential DR model and the driving profiles, the charging process is discretized using 15 minute segments and a constant charging power is assumed. For the 11 kW case this translates to a maximum charge amount of $\overline{\phi}_v = 2.75$ kWh per time slot. For each EV v the empirical driving profiles of the German Mobility Panel provide a consumption vector $\Gamma_v = (\gamma_v^1, \ldots, \gamma_v^T)$ specifying the driving energy requirement (kWh) in time slot t (distance from driving profile times electricity consumption of 0.15 kWh/km). In addition, the empirical profiles provide information about a vehicle's location, specifying possible charging locations given by a vector $A_v = (a_v^1, \ldots, a_v^T)$ with $a_v^t \in \{0, 1\}$ describing in which time slots a vehicle v is connected to the grid and able to charge ($a_v^t = 1$). Charging of EVs can be represented as charging vectors $\Phi_v = (\phi_v^1, \ldots, \phi_v^T)$. Since EVs can only be charged when connected to the grid, the vector A_v governs the current charging capacity and the following ϕ^t domains obtain:

$$\phi_v^t \in [0, a_v^t \overline{\phi}_v]. \tag{3.16}$$

The maximum battery capacity is given by $\overline{b}_v$ and assumed to equal 30 kWh. The battery State-Of-Charge (SOC) is tracked via the vector $\Psi_v = (\psi_v^1, \ldots, \psi_v^T)$, where $\psi_v^t \in [0, 1]$ represents the share of the battery capacity. Thus, each vehicle can be described by a tuple $v = (\Gamma_v, A_v, \Phi_v, \overline{\phi}_v, \Psi_v, \overline{b}_v)$. Given these properties and an appropriate objective, e.g., charging cost minimization, a charging strategy determines individual charging amounts Φ_v.

Simple Charging The simplest behavior of EVs is to charge whenever possible with the maximum charging amount available (AFAP). The charging amount under AFAP in one time slot is given by

$$\phi_v^t = \min\left\{\overline{\phi}_v a_v^t, \overline{b}_v - \psi_v^t \overline{b}_v\right\}. \tag{3.17}$$

Smart Charging A charging program characterizes the charging amounts ϕ_v^t per vehicle and time slot. Irrespective the objective, a valid charge program needs to schedule charging of EVs over the course of the simulation horizon to meeting the trip requirements of the driving profiles:

$$\psi_v^t \overline{b}_v = \psi_v^{t-1} \overline{b}_v + \phi_v^t - \gamma_v^t. \tag{3.18}$$

Objectives for scheduling EV charging might include, for example, a reduction of emissions, charging costs or grid utilization. To avoid simulation artifacts initial SOC ψ_v^0 and terminal SOC ψ_v^T are set to the same level:

$$\psi_v^0 = \psi_v^T. \tag{3.19}$$

Condition 3.19 prevents the optimization from fully discharging the battery at the end of the optimization horizon. A value of $\psi_v^0 = 0.3$ is assumed for the initial SOC of EVs.

Total Population Consumption

Consumption for all electric vehicles L_V^t in time slot t is given by:

$$L_V^t = \sum_{v \in \mathcal{V}} \phi_v^t. \tag{3.20}$$

Model Extensions

Such a simple smart EV charging model allows to identify potentials of distinct coordination approaches for EV charging by aligning mobility requirements, technical specifications, and charging activity. Yet, the model facilitates maximal flexibility for charging of EVs and might lead to an overestimation of benefits in the power system and cost savings potentials of the user. Consideration of user interests (e.g., spontaneous trip range or battery wear), and technical details of the charging process might be of interest to improve model adequacy.

User Interests Scheduling of EV charging, as presented in the smart charging model, can exhibit discharging to low SOC levels, e.g., to exploit cheap electricity prices at later times. Such SOC trajectories are unwanted by EV users, as they prohibit spontaneous trips. To avoid this undesired behavior, ideally, vehicles start charging if the SOC drops below a certain threshold level $\underline{\psi}$. According to Flath et al. (2012), adding an additional constraint to the model can trigger charging below a SOC threshold level (for all $v \in \mathcal{V}$ and $t \in [T]$):

$$\phi_v^t \geq a_v^t \, \overline{\phi}_v \, \frac{\underline{\psi} - \psi_v^t}{\underline{\psi}}. \tag{3.21}$$

Charging activity triggered by Condition 3.21 varies with the spread of the current SOC and the specified minimum battery level. Thus, higher charging power is applied for lower SOC levels reflecting the urgency of charging. At the same time, this formulation retains linear program properties facilitating an efficient calculation of the model. Within this thesis a value of $\underline{\psi} = 0.3$ is assumed for the SOC threshold level. See Flath et al. (2012) for a more intensive discussion and a sensitivity analysis of SOC thresholds.

For EVs the battery is the sole on-board power source. Thermal heating and cooling requirements have to be covered by the battery resulting in lower range for driving and additional battery wear. Battery usage for cooling and heating can be reduced via preconditioning of EV cabin or battery before a trip using power from the electricity grid. Barnitt et al. (2010) estimate a 10 minute period for preconditioning with average power of 3 kW for cooling and 4 kW for heating. Looking at the still prevailing barrier range anxiety poses for EV adoption, preconditioning might be interesting to face range anxiety and reduce battery wear. Yet, the energy needs for preconditioning correspond to about 2 % of the average battery capacity of current EVs. For new generation of batteries with even higher capacity and increased life time the moderate importance of preconditioning for EV range can be expected to decrease. Therefore, it is not included in the EV charging model.

Battery Wear Battery technology is crucial for the large-scale role out of EVs. Batteries are costly and due to missing experiences on wear and life expectancies might circumvent EV purchases. Some car manufacturers take the risk of battery wear and offer a leasing model[19] or guarantee life time and minimum range[20]. Charging also effects battery lifetime and could be considered for a more realistic model of charging flexibility to minimize wear of lithium-ion batteries. Charge rate and SOC are the main drivers for battery wear (Han et al., 2014). Due to the low C-rates[21] for the IEC charging modes (C-rates between 0.12 and 0.73) the impact of SOC on battery wear is dominating and effects of the charge rate can be neglected (Bashash et al., 2011).

Most lithium-ion batteries suffer stress at high and low SOC levels (Han et al., 2014). Bashash et al. (2011) present an EV charging model integrating the impact of SOC on battery health. Their approach allows to exploit the full battery capacity as it balances between energy costs and battery wear. However, it requires a detailed and complex lithium-ion battery model and multi-objective optimization. To retain linearity of the optimization programs an action some EV manufacturers undertake to prolong battery life time can be came back to. They limit the available charge and discharge level of the battery (Marra et al., 2010). Such a model with restricted battery capacity can establish a lower benchmark for charging flexibility and vehicle range.

Technical Characteristics The basic model disregards technical characteristics of EV charging and assumes a linear increase of the SOC based on charging power. In reality, EV battery charging is performed with constant current only until the maximum cell voltage is reached. Then, fully charging the battery takes place with constant voltage, resulting in a non-linear increase of the SOC. Switching from constant current to constant voltage within the charging process appears at the maximum cell voltage, i.e., at high SOC levels. Thus, a limit on the available battery capacity also avoids the constant voltage phase during charging, keeping the EV model linear (Marra et al., 2012).

[19] http://www.renault.de/renault-modellpalette/ze-elektrofahrzeuge/zoe/zoe/preise-und-technische-daten/

[20] http://www.teslamotors.com/de_DE/models/design

[21] capacity-normalized charging speed ($\frac{\text{battery capacity}}{1h}$)

Another technical aspect are losses in the charging process. Losses scale quadratically in charging current ($P_{loss} = I^2R$). Hence, there is a trade-off between charging speed and charging efficiency. However, internal resistance of modern EV batteries is very low. Amoroso and Cappuccino (2012), report a limited decline in charging efficiency for C-rates below 1.0 with efficiency ranging from 0.99 at 0.1 C to 0.91 at 1.0 C. The applied charging power of 11 kW results in a C-rate of 0.37. Due to this very low C-rate, in the EV model a loss-free charging process with efficiency $\eta_v = 1$ is assumed.

3.6 Scope of Supply Models

The demand models previously described represent DR behavior of residential customers. Yet, to assess the impact of DR in the power system a representation of the supply side is required. For such a supply model the trade-off between complexity and adequacy arises once again. Existing generation models can provide some guidance to balance these contrary requirements. In the following, a brief overview of supply side representations in scientific literature is given.

Several researchers completely neglect the supply side and apply basic load parameters to assess DR effects. Typically the focus in these publications is on peak load reduction. For evaluation load duration curves (Ramchurn et al., 2011) or peak-to-average ratio (Shinwari et al., 2012) are used. Others deploy comprehensive supply models integrating real-world plant configurations. In the work of van Vliet et al. (2010) plant capacities and generation costs establish a merit order to dispatch generation units. Sioshansi (2012) formulates a unit commitment problem to determine the least-cost schedule of generation units in one region.

In another stream of research stylized supply side models are used to evaluate optimized operation strategies of dispatchable units for improving integration of intermittent renewable generation. Varaiya et al. (2011) establish a generation model focusing on adequacy of generation to meet load requirements. Hooshmand et al. (2013) provide a dispatch model incorporating constraints for plant characteristics and distribution grid capacity.

Investigations with a focus on DR for the integration of renewable energy sources show a broad range of detail in supply side representation. The most basic approaches assume static output time series of intermittent generators and schedule flexible loads to fit these profiles. To evaluate the improvements in power system efficiency utilization levels of renewable generation (Subramanian et al., 2012), deviation between load and generation (van den Briel et al., 2013) or imbalance costs (Vandael et al., 2011) are considered. A stylized supply side model is provided by Grünewald et al. (2015). They assume a merit order stack with different classes of generation units (e.g., intermittent renewable generation or baseload plants) to derive costs of electricity generation under different retail price regimes. Göransson et al. (2010) and Wang et al. (2011) employ real-world plant configurations to assess effects of flexible loads, e.g., Plug-in Hybrid Electric Vehicles (PHEVs), in a power system with high wind shares. Such comprehensive supply side models enable to evaluate the effects of DR on costs and emissions in a regional power system. Yet, to calibrate generation units they require detailed real-world data on power plant characteristics.

3.7 Supply Model

This section describes a reference power system for the evaluation of DR effects. To retain a clear focus on load flexibility potentials and coordination mechanisms, it is abstracted from a comprehensive supply side model and a stylized power system is used. Acknowledging the potentials of residential DR for the integration of renewable generation, a reference power system with a high wind and PV share is assumed. In this system renewable energy sources supply residential load of households, stationary batteries and EVs. Load exceeding renewable generation (residual load) needs to be supplied by dispatchable conventional units. Empirical wind and PV generation data are scaled to match the total consumption.[22] In the following, these empirical output profiles are characterized and the accuracy of available wind and PV generation forecasts is discussed. Further, the stylized power system, which enables to evaluate DR effects on the supply side, is presented in more detail.

[22]Modeling of generation output provides another option to integrate intermittent renewable sources in the supply model. For wind such a model is provided, for example, by Keles (2013).

3.7.1 Renewable Generation Input Data

Renewable generation and day-ahead forecast data employed covers wind and PV time series from German TSOs in 15-minute resolution. Wind data is obtained from the balancing zone of 50Hertz[23] and PV data from Transnet BW[24]. Missing data points are estimated using linear interpolation of available adjacent values. The subsequent analysis of the empirical generation and forecast data helps to better understand the challenges renewable generators might pose in the power system.

Generation Characteristics

During the last years major renewable generation capacities have been installed. In the two balancing zones serving as data sources at the end of 2013 13.5 GW wind (50 Hertz) and 4.7 GW PV (Transnet BW) have been installed. Electricity generation of wind and PV is directly affected by the current weather conditions. Thus, the resulting output of both sources is highly volatile as shown in Figure 3.7. The boxplots for the hourly values are based on empirical generation data of the two balancing zones for the years 2012 and 2013. To facilitate a clear presentation outliers are not depicted in the boxplots. Despite the influence of clouds and sunshine periods, PV generation follows some basic patterns with a peak about noon. Yet, the uncertainty rests in the height of the daily amplitude which can vary to a great extent between days. In contrast, wind generation does not show a pronounced pattern. Only a small drop during the morning hours and a slight increase in the night hours can be observed.

Table 3.8 gives an overview of basic summary statistics and output variations for the empirical wind and PV data. Looking at the median values the intermittent characteristics in PV and wind output can be observed. During half of the time slots no or only limited renewable output is available. Meanwhile, in the peak generation hours up to 3.7 GW PV and 13.5 GW wind power is provided. In addition, the table shows rapid changes in output levels for PV and wind, thus, emphasizing their high short term volatility. In the two balancing zones PV generation can vary by up

[23] `http://www.50hertz.com/de/Netzkennzahlen.htm`
[24] `http://www.transnetbw.de/de/kennzahlen`

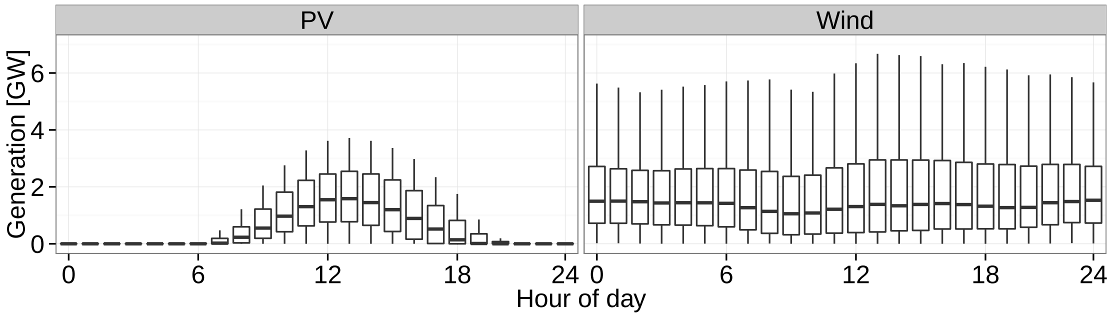

Figure 3.7: Variation of generation output per hour

to 0.8 GW in 15-minutes and by 0.9 GW in one hour. Wind output changes up to 1.4 GW in 15-minutes and up to 1.9 GW in one hour.

Table 3.8: Summary statistics and output variation within 15-minutes and one hour for PV and wind data (all values in [GW])

			Summary statistics				Output variation			
	Year	Cap*	Max	Mean	Median	SD	Up15	Down15	Up1h	Down1h
PV	2012	4.1	3.7	0.5	0	0.8	0.3	-0.4	0.7	-0.9
	2013	4.7	3.7	0.5	0	0.9	0.4	-0.8	0.9	-0.9
Wind	2012	12.4	10.2	2.1	1.5	2.1	1.0	-0.9	1.9	-1.7
	2013	13.5	11.1	2.1	1.4	2.1	1.4	-0.9	1.8	-1.9

*Generation capacity installed at the end of the year

The average monthly output (see Figure 3.8) shows seasonal variations for both generation technologies. PV achieves higher output during summer and the lowest levels during winter months. Longer day periods in summer provide an explanation for higher PV generation in summer. In contrast, wind turbines have the highest generation output in winter. Moreover, large differences in generation output between different years can be observed in the figure. Overall, the short and long term variations in wind and PV generation call for large reserves of dispatchable generation units to guarantee system stability.[25] To reduce reserve requirements residential DR is a promising option to facilitate the integration of renewable sources and maintain balance between demand and supply on short term. Obviously, flexible residential loads do not allow to address seasonal or yearly variations in renewable

[25]A more detailed investigation on effects and costs of intermittent generation in a power system is provided by Skea et al. (2007).

generation output and should be complemented by long term storage such as power to gas (Schuller et al., 2015).

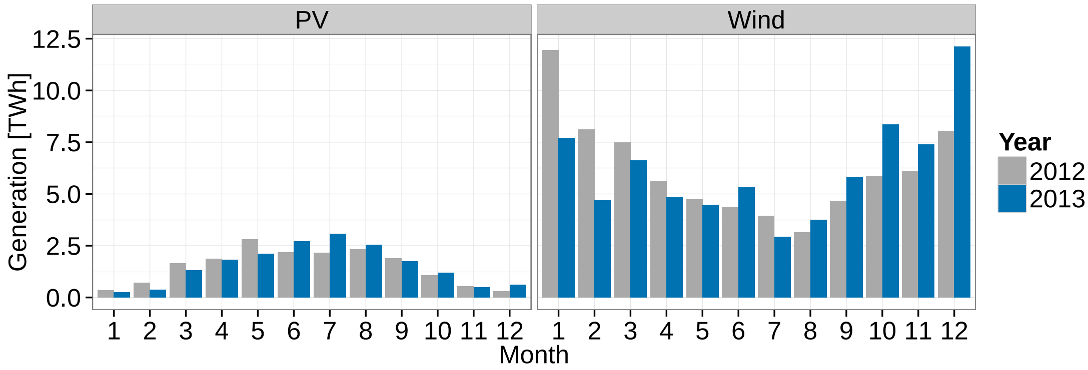

Figure 3.8: Monthly PV generation for the Transnet BW and wind generation for the 50Hertz balancing area for 2012 and 2013

Accuracy of Generation Forecasts

Forecasts of renewable generation allow to schedule flexible loads and other generation units in advance. The accuracy of these forecasts is important to decrease deviations from the original schedule and thus reduce requirements for real-time adaption (Klobasa, 2009). TSOs in Germany use forecasts for wind and PV generation on a day-ahead basis in their balancing area. This data is publicly available and within this thesis applied to represent renewable generation forecasts. Figure 3.9 depicts forecast and generation data for one example week of the two intermittent generation technologies. In the figure it can be observed that PV forecasts match the general output pattern and only small deviations in the morning and afternoon hours take place. Yet, the height of the daily PV amplitude around noon is often missed by predictions. The right panel of the figure shows that overall wind prediction meets the real generation very well. In comparison to PV, forecasts for wind deviate to a smaller extent from real generation, but deviations take place more frequently.

These findings are supported by the density plots in Figure 3.10. To create this figure data on forecast errors are normalized by the installed generation capacity and PV night hours without generation are excluded. Positive values indicate situations

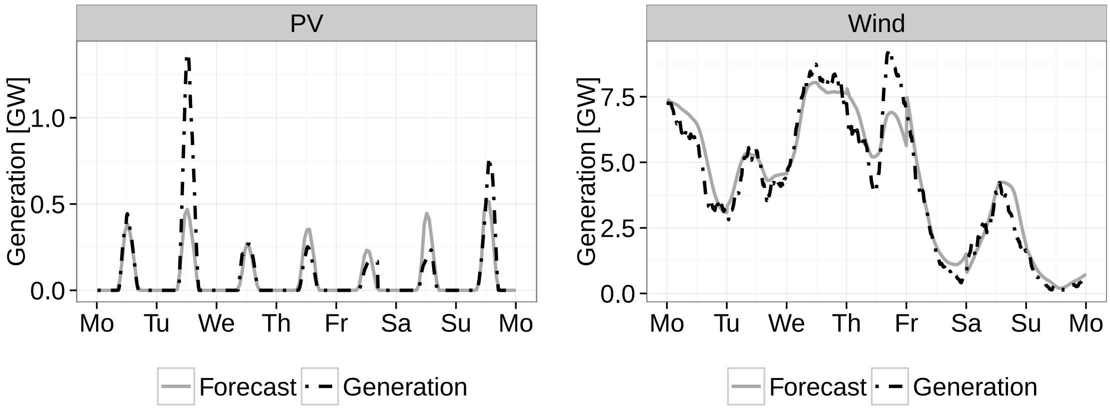

Figure 3.9: PV and wind forecast and generation for one example week

in which realized generation exceeds the forecast output level. For PV good predictions and large deviations occur more frequently as compared to wind generation. Wind predictions more often show deviations of medium size.

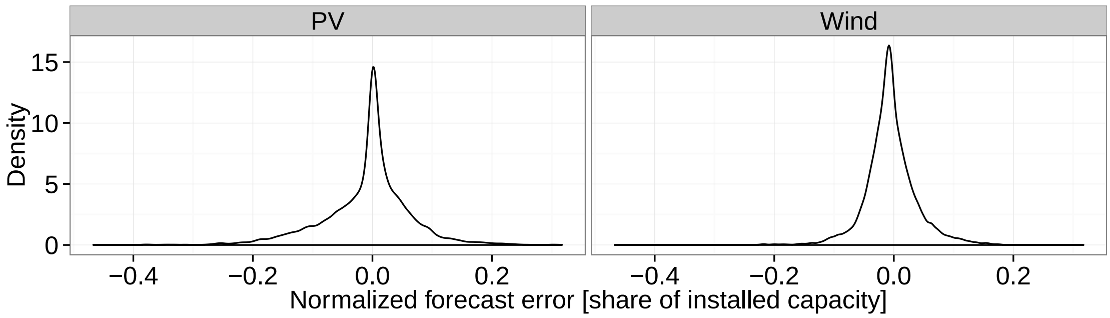

Figure 3.10: Normalized forecast error for PV and wind generation for 2013

3.7.2 Stylized Power System

For the impact analysis of residential DR a power system with a large share of volatile renewable generation G_{RES} is assumed.[26] For this purpose wind and PV generation are rescaled to match the total consumption during the simulation period. This way the volatile characteristics of intermittent generation are represented by

[26]The description of the stylized power system and the conventional generation model in this section are also used in our working paper Flath and Gottwalt (2014).

empirical inputs. Due to the scaling the main property of the empirical data for the simulation is the relative variation bandwidth. Today, some regional power systems already show high shares of volatile renewable generation. One real-world example for such a power system would be Western Denmark where wind turbines make a large amount of the installed power generation capacity (Göransson and Johnsson, 2009).

The residential load in the system comprises fixed household base load[27] b and flexible loads of household appliances L_{FH} and electric vehicles L_V. Stationary batteries can either supply or consume electricity. Their load is denoted by L_S. In the presence of inflexible base load b, $G_{RES} - b$ is the net renewable generation, where positive values indicate renewable generation available for flexible loads (see Figure 3.11 for one example week). Note that net renewable generation can also take negative values.

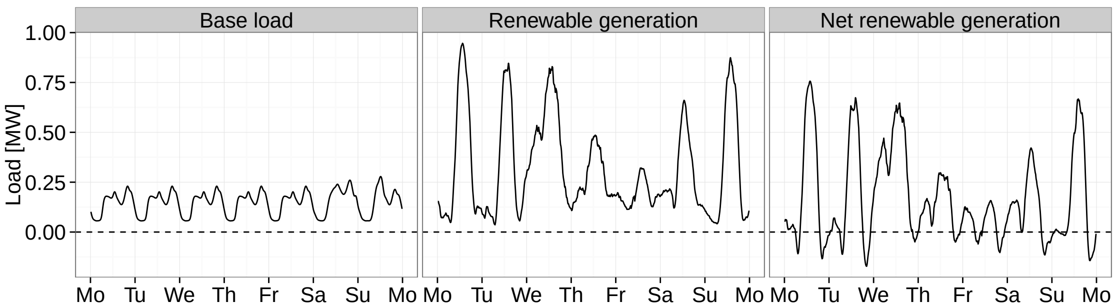

Figure 3.11: Base load (b), renewable generation (G_{RES}) and net renewable generation ($G_{RES} - b$) for one example week

Typically generators in the power system are dispatched in order of increasing marginal generation costs (Stoft, 2002). Thus, from an economic perspective it is optimal to first use electricity from renewable sources, as their marginal costs of generation are very low. In a power system with a large share of volatile renewable generation, flexible load should ideally be scheduled such that the residual load L', which needs to be covered through costly conventional generation G_C, is minimized. Residual load is defined by $L' = b + L_{FH} + L_S + L_V - G_{RES}$. To avoid dispatch of expensive generators and to reduce required generation capacity in the system residual load should be evenly distributed.

[27] Based on the standardized household load profiles from the German utility association.

Conventional Generation Model

Cost-aware coordination of flexible loads entails two sub-objectives: (i) reducing total conventional generation usage (energy) and (ii) limiting instantaneous peaks of residual (power).[28] For DR evaluation these dimensions are considered isolated for a high-level assessment of the coordination properties and in a more comprehensive, integrated way based on a dispatch model with an embedded generation cost function $C(L')$. To this end, a stepwise increasing linear function which mimics the merit order curve is applied (Sensfuss et al., 2008).[29]

The power system model is formulated as a linear program minimizing variable costs of conventional generation. For all simulation times $t \in [T]$ the following objective function is obtained:

$$\min \sum_{t} C\left(G_C^t\right) \tag{3.22}$$

The balance between generation and demand is ensured through the following constraint:

$$\forall t \in [T] : G_C^t + G_{RES}^t - L_{FH}^t - L_S^t - L_V^t - b^t \geq 0. \tag{3.23}$$

It requires the total generation from renewable and conventional generators to cover total electricity demand in each time slot. In a system with a large share of renewable energy sources generation output might exceed load and available storage potential. For such situations curtailment of renewable output is an option to guarantee system stability. Thus, in-line with Varaiya et al. (2011) the balancing constraint only requires generation adequacy (generation $\geq$ demand) instead of strict equality reflecting the shedding potential of renewable generators.

Model extensions

In economics the term non-convexity is applied to describe a market with discrete choices (Scarf, 1994). The electric power market is a prominent example for such

[28] Clearly, the two are directly connected as total generation is the integral over instantaneous load.
[29] Breakpoints of the piecewise linear function are assumed every 40 kW. At each breakpoint the slope (i.e., variable costs) increases by 2.5 monetary units.

a market. Non-convexities arise from the operation properties of generators, e.g., start-up and shut-down costs as well as minimum output requirements . The lumpiness of the costs in the electric power market can largely influence the operation of conventional generators (O'Neill et al., 2005). For example, Sioshansi et al. (2010) show that exogenously specified electricity rates can properly signal the marginal cost of generation, but do not convey non-convex start-up costs of generators. To retain a clear focus on the load coordination aspect and to avoid further assumptions, this work abstracts from further constraints like ramping or grid/ substation capacity. However, these can be easily embedded in the stylized dispatch model (see, e.g., Hooshmand et al., 2013).

Chapter 4

Flexibility of Residential Loads

This chapter focuses on the *potential* of incentive based DR programs in a residential area to support the integration of renewable generation. The analysis builds on the demand and supply model presented in the previous chapter. Combining flexible loads and volatile RES in one portfolio allows to harness synergies. A designated entity typically referred to as “aggregator” or “load controller” can directly schedule these flexible loads to increase coverage of demand by renewable generation and reduce requirements for additional conventional generation. Under direct load control the aggregator centrally creates a schedule for the flexible loads. Thus, the evaluation establishes an upper benchmark.

In the first part, this chapter provides decision support for aggregators on different levels. For *operational* control of flexible loads the importance of information availability (forecast quality, lookahead times) for scheduling is analyzed. A large amount of flexible loads in the portfolio of an aggregator might not be enough to balance load and generation. Thus, to establish some guidelines for the portfolio composition of an aggregator the impact of customer (*tactical level*) and renewable generation (*strategic level*) variations is investigated.

Residential households can expect some form of incentive payments for the provision of load flexibility to the aggregator (Albadi and El-Saadany, 2008). In the second part of this chapter, the value of individual devices for DR is estimated and serves to identify customers that can benefit from participating in such programs. The value of individual devices for DR also serves to identify key features characterizing load flexibility and to prioritize flexible loads for DR applications.

Section 4.1 provides a short overview of centralized optimization approaches in power system analysis with a focus on demand response. Section 4.2 describes a model to assess effects of direct load control and sketches possible applications. A base evaluation scenario is described in Section 4.3. Subsequently, one example week illustrates the effects of direct load control for flexible loads (Section 4.4). Section 4.5 investigates how information availability and portfolio composition affects load balancing potentials of flexible demand. Section 4.6 takes a closer look at the opportunities of DR for residential customers and identifies potential winners and losers. In addition, key dimensions of flexibility are determined. Finally, Section 4.7 concludes and summarizes the main implications of this chapter.

The integrated optimization model employed extends the joint work from Gottwalt et al. (2013) by including flexible residential household appliances.

4.1 Related Work

Optimization in the power system has a long history in dispatching of generation resources. In the unit commitment problem the system operator determines the least-cost scheduling of generation units to meet electricity demand. Long-term unit commitment problems for entire regions can lead to high computing times. Thus, various approaches for generation scheduling are applied, e.g., mixed integer programming (Li and Shahidehpour, 2005) or particle swarm optimization (del Valle et al., 2008). A bibliographical survey on methods to solve unit commitment problems is provided by Padhy (2004).

Recently, flexible residential demand has been integrated in these models to assess the effects on costs and green house gas emissions in traditional power systems (Sioshansi et al., 2010; van Vliet et al., 2010). A unit commitment model to assess cost reductions via flexible residential demand in a future power system with high shares of fluctuating RES is provided by Göransson et al. (2010) and Wang et al. (2011). Most researchers neglect household appliances in their studies and focus on exemplary use of EV charging as these loads are large and flexible.

To avoid the complexity of centralized optimization on the system level, several researchers apply hierarchical coordination procedures. To this end, they split the general optimization problem into several smaller subsets controlled by local entities (Li et al., 2012). On the local level aggregators schedule flexible demand—often with the objective to reduce peaks or reduce power quality problems. In addition, the local aggregators receive signals from superordinated controllers, e.g., to prevent stability threats (Galus et al., 2012) or to facilitate load balancing on higher grid levels (Vandael et al., 2011).

Furthermore, centralized load control is applied to study potentials of flexible residential demand for specific system parts. The maximization of distribution grid losses is a case in point (Clement et al., 2009; Acha et al., 2010). Direct control of EV fleets or HVAC pools for power system regulation is another scenario considered (Andersson et al., 2010; Caramanis and Foster, 2009; Sullivan et al., 2013). Tushar et al. (2014) investigate the control of residential demand to increase electricity autarky of a community. They schedule residential loads and EV charging trying to minimize electricity imports for a community with a high share of RES.

4.2 Direct Load Control Model

Household appliances, EVs, and stationary batteries are incorporated in the demand model. This comprehensive approach allows a broad assessment of various DR potentials to support the integration of volatile and uncertain renewable energy sources. The centralized control model and the simulation process are described in more detail in this section. Furthermore, concrete application scenarios of such a model are discussed.

4.2.1 Formalized Description

Integrated optimization of device scheduling and generation dispatch can be formulated as a mixed-integer linear program. Decision variables, objective function and constraints of this formulation are described in the following. For a more detailed description of the individual models, it is referred to the Sections 3.3.3, 3.4.2, and 3.5.3 for the demand side and to Section 3.7.2 for the supply side.[1]

Decision Variables

The goal of the optimization model is to schedule household appliances, EV charging, and battery storage for all simulation times $t \in [T]$ such that the maximum amount of electricity for their operation is provided from renewable sources. Optimal runtimes for household appliances are characterized by the binary variables x_a^t for appliances $a \in \mathcal{A}$, x_b^t for appliances $b \in \mathcal{B}$ and x_r^t for run $r \in R_c$ of appliance $c \in \mathcal{C}$. An optimal charging program characterizes the charging or discharging amount ϕ_s^t for a stationary battery $s \in \mathcal{S}$ and the charging amount ϕ_v^t for an electric vehicle $v \in \mathcal{V}$ for each time slot. As stationary batteries can feed electricity back to the grid, the charging or discharging amount is restricted to the interval $\phi_s^t \in [\underline{\phi}_s, \overline{\phi}_s]$. In contrast, for EV charging only positive charging amounts are possible $\phi_v^t \in [0, a_v^t \overline{\phi}_v]$. Remember that a_v^t indicates the available charging capacity at the vehicle's location for a time slot. Whenever consumption exceeds supply from renewable sources, conventional generation has to be used. On the supply side the continuous decision variable is G_C^t for the energy that needs to be delivered by conventional generation.

Objective Function

The objective of the integrated device scheduling and generation dispatch model[2] is the minimization of variable generation costs $c^v(G_C^t)$ while ensuring power system and device constraints:

$$\min_{x,\phi,G_C} \sum_{t=1}^{T} c^v \left(G_C^t \right)$$

with $(x, \phi, G_C) \in \mathbb{B} \times \mathbb{R} \times \mathbb{R}_+$.

[1] A basic version of the integrated optimization model focusing on EVs as flexible load has been presented in the joint work of Gottwalt et al. (2013).

[2] See Code B.1 in the Appendix for an ILOG OPL example specification of the optimization problem using a semi-automatically controlled appliance.

Constraints

To ensure the feasibility of the decision variables several constraints apply. A valid solution requires total generation from conventional plants (G_C^t) and from renewable energy sources (G_{RES}^t) to match the electricity demand of households, stationary batteries and EVs in any time slot. Bear in mind that the consumption of an active household appliance $a \in \mathcal{A}$ and $b \in \mathcal{B}$ is denoted by ρ. Thus, the following equation guarantees demand coverage:

$$\begin{aligned} G_C^t + G_{RES}^t - \sum_{a\in\mathcal{A}} x_a^t \rho_a - \sum_{b\in\mathcal{B}} x_b^t \rho_b \\ - \sum_{c\in\mathcal{C}} \sum_{r\in R_c} \sum_{k=1}^{t} \Big(x_r^k \cdot P_r\left(t+1-k\right)\Big) - \sum_{s\in\mathcal{S}} \phi_s^t - \sum_{v\in\mathcal{V}} \phi_v^t - b^t \geq 0. \quad (4.1) \end{aligned}$$

For the ease of reading the definitions of the flexible devices are repeated in the following. The simulation horizon T is divided in $C_a \in \mathbb{N}$ intervals for appliances $a \in \mathcal{A}$ and the number of activation slots per operation or appliance has to be specified to prevent the optimization from curtailing run durations. Condition 3.2 ensures that runs of these appliances fit the required duration δ_a in each flexibility interval $[s_a^i, e_a^i]$:

$$\forall i \in [C_a] : \sum_{t=s_a^i}^{e_a^i} x_a^t = \delta_a. \qquad \text{(3.2 revisited)}$$

Similar, for appliances $b \in \mathcal{B}$ the simulation horizon T is divided into C_b intervals and Condition 3.4 ensures activation of each operation $i \in C_b$ in the corresponding flexibility interval $[s_b^i, e_b^i]$:

$$\forall i \in [C_b] : \sum_{t=s_b^i}^{e_b^i} x_b^t = 1. \qquad \text{(3.4 revisited)}$$

Condition 3.8 ensures the start of a run $r \in R_c$ of appliance $c \in \mathcal{C}$ in the flexibility interval $[t_r^s, t_r^l]$:

$$\sum_{t=t_r^s}^{t_r^l} x_r^t = 1. \qquad \text{(3.8 revisited)}$$

For the same appliance type $P_r = (\rho_r^1, \ldots, \rho_r^{\delta_r})$ defines the consumption profile and the load of an operation is given by:

$$P_r(\tau) = \begin{cases} \rho_r^\tau, & \tau \in \{1, \ldots, \delta_r\} \\ 0, & \text{otherwise.} \end{cases} \tag{3.10 revisited}$$

For a stationary battery $s \in \mathcal{S}$ the SOC (ψ_s^t) at time t is determined by the battery level in $t-1$ and the charging or discharging (ϕ_s^t) amounts:

$$\psi_s^t \overline{b}_s = \psi_s^{t-1} \overline{b}_s + \phi_s^t. \tag{3.13 revisited}$$

In addition, a terminal battery level ψ_s^T has to be specified to prevent optimization from completely discharging the battery towards the end of the time horizon:

$$\psi_s^0 = \psi_s^T. \tag{3.14 revisited}$$

In a similar fashion Constraints 3.18 and 3.19 capture EV charging. The former ensures continuity of the battery level (ψ_v^t) of each vehicle over time by linking charging amounts (ϕ_v^t), driving consumption (γ_v^t), and the battery level in $t-1$:

$$\psi_v^t \overline{b}_v = \psi_v^{t-1} \overline{b}_v + \phi_v^t - \gamma_v^t. \tag{3.18 revisited}$$

The latter constraint specifies initial and terminal SOC which typically are set to a common level:

$$\psi_v^0 = \psi_v^T. \tag{3.19 revisited}$$

4.2.2 Solution Procedure & Workflow

For the analysis of DR potentials two basic simulation configurations are applied. First, full information on appliance and charging flexibility, renewable generation output, and power system characteristics is assumed. The left panel of Figure 4.1 depicts the simulation flow for the integrated optimal scheduling and Conventional Generation (CG) dispatch model under full information. Historic Renewable Geneation (RG) time series are used as input.

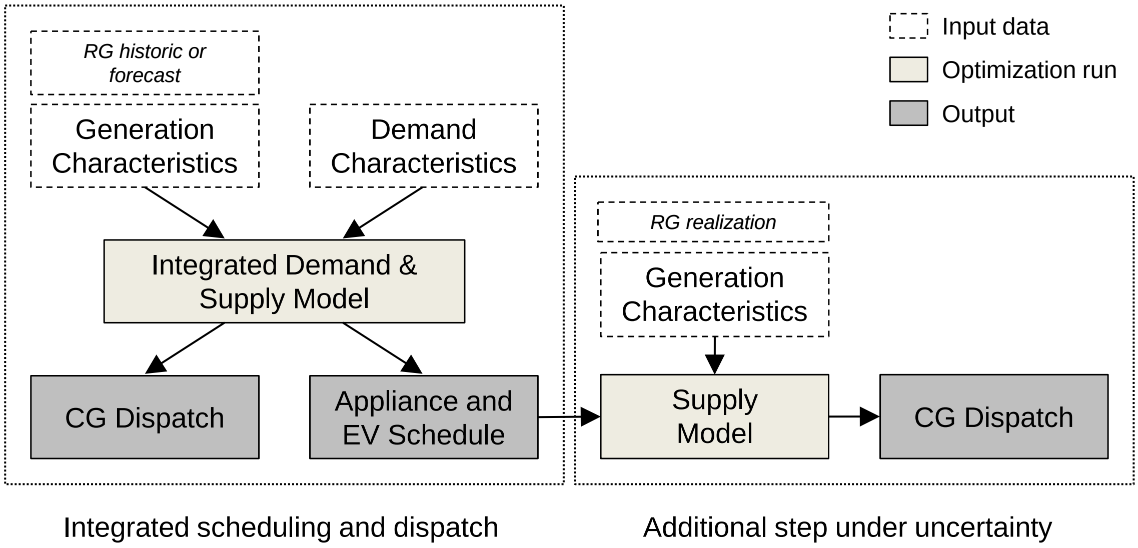

Figure 4.1: Overview of simulation flow for direct load control (with and without uncertainty in renewable generation output)

In the second configuration renewable generation output is not exactly known in advance and the simulation requires an additional step (see right panel of the figure). For this purpose, the integrated model is executed with forecasts of renewable generation to build the schedule of appliance operations and EV charging. Then, the supply model is executed again using the real renewable generation output and the schedule determined under generation forecasts to dispatch conventional generation and to estimate system costs.

To be able to efficiently evaluate power system effects of flexible residential demand in a variety of scenarios an approach integrating JAVA for data handling (input and output) and problem modeling, IBM ILOG CPLEX 12.5 for optimization runs, and the statistical software R for visualization and analysis of the output data is used.

4.2.3 Performance

The software package CPLEX is used to solve the integrated model and schedule consumption of devices and dispatch generation. Computational complexity is considered as a standard drawback of centralized regimes and may impede solving large-scale problems. Runtime for a single optimization of the integrated model is driven by the optimization horizon, the population size, and the set of flexible appliances that are scheduled. For scheduling of flexible appliances, EVs and battery storage the optimization horizon ideally should be chosen between one day and one week. Shorter horizons require adaptions of the JAVA model implementation to avoid end of horizon effects. Longer optimization horizons do not provide much new insights but lead to increasing runtimes.

The impact of optimization horizon and population size as well as the set of flexible appliances on simulation runtime is shown in Table 4.1.[3] The table includes the number of problem variables and constraints, which drive runtime for the distinct problem sizes. Runtime estimations presented in the table are based on five replications of the simulation. It can be observed that the number of problem variables and constraints increase linear in the population size. The non-linear increase for a larger optimization horizon is due to the modeling approach for appliances in group $\mathcal{C}$. For these appliances the number of runs r and the length of the vector X_r which indicates the start of a run both go up with a larger optimization horizon.

A schedule for the full set of flexible devices of 10,000 households including EVs and stationary batteries over a horizon of one day can be calculated in about 350 seconds. The same population size for a weekly optimization horizon has about 43 million constraints and becomes computationally intractable due to memory requirements.[4] Thus, simulations for larger populations can only be conducted by reducing the number of flexible appliances, with the current mixed-integer formulation, the applied solver and the hardware in use. A smaller set of flexible appliances, e.g., only storage space and water heaters, enables optimization of a day or a week for 100,000 households.

Note, that for all optimization runs in this thesis an optimality tolerance of 1 % is used. This gap reduces runtime for daily optimization by 20 % and for weekly optimization by 90 % meanwhile quality of the solution is only slightly affected.[5]

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[3]Simulations are performed on an Intel(R) Core(TM) i5-3470 CPU with 8 GB RAM operating on Windows 7 Professional 64 Bit.

[4]A rough estimation for the lower bound of memory use in CPLEX is given by one gigabyte per million constraints for integer programs.

[5] CPLEX calculates a high-quality solution and proves the optimality of that solution. A high-

Table 4.1: Average simulation runtimes, number of problem variables and number of constraints for various optimization scenarios of dircet load control

		Optimization horizon					
		Day			Week		
Pop. size	Flexible Appliances	Avg. run-time [s]	Variables [$\times 10^3$]	Constr. [$\times 10^3$]	Avg. run-time [s]	Variables [$\times 10^3$]	Constr. [$\times 10^3$]
10	Full set	0.5	3.0	3.0	1.2	55.1	53.5
100	Full set	0.7	29.1	23.4	11.0	489.9	550.0
1,000	Full set	11.1	284.1	225.3	341.5	4,824	4,410
10,000	Full set	344.2	2,838	2,246	Out of memory		42,900*
100,000	Stor. heater	85.0	1,152	8.1	716.0	8,067	88.0

*Estimated number of constraints

4.2.4 Model Applications

The integrated model allows to assess balancing potentials of flexible loads under direct load control. Given the large number of applications facilitated by such a model, suitable evaluation scenarios have to be chosen. The model can be applied to analyze overall effects in a future power system with a large share of renewable generation and flexible loads in the style of Göransson et al. (2010). This typically requires an extrapolation of the results of a small representative population to system level (see Ramchurn et al., 2011 or Kamper, 2010). The supply side representation facilitates an analysis of variable generation costs in the power system using a merit-order based cost function. For a power system analysis dispatch of individual plants might be of interest, e.g., integration of a comprehensive unit commitment model.

The idea of a load aggregator, which bundles the capacities of various households, is another possible analysis scenario for a centralized control regime. Such an aggregator has to supply its customers. For this purpose the central entity must buy electricity on the power market or contract generators (Schuller, 2014). An electric utility acting in an environment with priority feed-in of renewable generation is an example for such an aggregator. Here, demand flexibility offers the potential to make use of available renewable generation and to avoid contracting of additional generation capacities in peak hours.

quality solution often can be found in a fraction of the time required to prove the optimum.

Finally, a microgrid of a small residential municipality is an interesting scenario for centralized control of residential household loads (Tushar et al., 2014). Such a community has a fixed installed capacity of volatile renewable energy sources (i.e., wind turbines and PV panels) and electricity demand of the municipal households is flexible. A central entity schedules these loads to utilize wind and PV generation reducing additional electricity required and thus minimizes the costs of electricity supply for the households. A microgrid scenario calls for the usage of local PV and wind generation data as for a small municipality forecasts are less accurate as compared to an entire region.

4.3 Model Setup

The previous section described a formal integrated load scheduling and dispatch model. In this section, parameter specifications for instantiating the base scenario of the model are given which is then applied to analyze balancing potentials of flexible demand for a load aggregator. Further, the generation of static load scenarios for comparison and the data evaluation approach are described. An overview of all demand and supply side parameters characterizing the base scenario is provided in Appendix B.

Demand Side – Device Shares and Population Size

The base evaluation scenario follows Kamper (2010) and simulates a population of 1,000 households. An EV share of 16 % is assumed which corresponds to the 6M EV target of the Federal Government of Germany (2011) for 2030. For decentralized battery storage the capacity prediction of Schlick et al. (2012) is extrapolated to 2030 resulting in a 2.5 % penetration level for the base scenario. For larger populations simulation runtime for the full set of flexible appliances increases and renders an evaluation of different scenarios and sensitivities computationally intractable.

Supply Side – Generation Portfolio and Simulation Horizon

For the base scenario a generation portfolio with a 50–50 mix of PV and wind is assumed. Historical renewable generation time series are scaled to match energy demand of EVs and households over the simulation period. Consequently, with fully flexible devices demand could be covered completely by PV and wind.

Electricity output of renewable generators differs largely between weeks (see Section 3.7.1). To incorporate these variations of generation output a reasonable assessment of flexible load potentials for the integration of PV and wind has to be based on a simulation horizon of several weeks. Analyzing flexible demand potentials over an entire year allows to capture seasonal differences in generation patterns. Again, optimization runtime is the limiting factor when determining the number of simulated weeks. As flexible residential loads are not capable to capture seasonal load variations, for the analysis the simulation is executed over twelve weeks. Over this horizon low and high wind and PV generation weeks can be covered, while simulation runtime remains manageable.

Simulation Flow – Solution Procedure Static Load

In addition to a central control regime, a static load scenario with uncontrolled appliances and EV charging is considered to assess efficiency gains due to flexible residential demand. In the absence of load control, it is assumed that EV charging activity is only governed by drivers' individual preferences. Hence, the simple strategy (AFAP) is applied to determine charging of the EVs. As a reminder, under an AFAP regime drivers maximize their EV's range by charging whenever possible with the maximum charging power available. Under a static load regime, i.e., in the absence of incentives or advanced strategies, it is assumed that batteries are not in use. In the uncontrolled scenario, first, appliance and EV loads have to be determined. Then, the supply side model is applied to derive conventional generation requirements supplying residential load and EV charging that are not covered by generation from renewable sources. Figure 4.2 illustrates the simulation flow for static demand in the absence of load control.

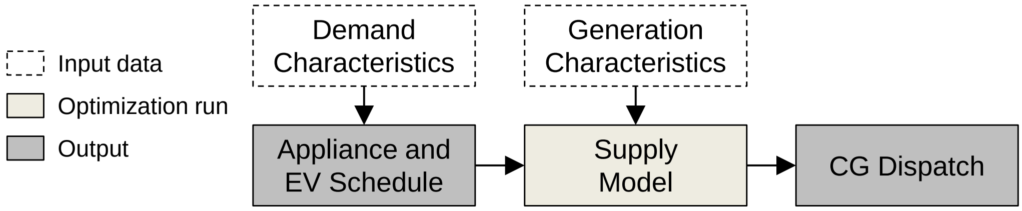


Figure 4.2: Overview of simulation flow for static demand

Output Data Analysis – Sampling

A simulation is a computer-based statistical sampling experiment. Consequently, appropriate techniques to analyze the output data are required (Law, 2011). The simulation of residential electricity demand uses random samples from probability distributions as starting points of appliance operations. Thus, a single simulation run only reflects a particular realization of these random variables. Results for a single realization may therefore deviate from the true characteristics due to input variance. Evaluations of the centralized control regime require repeated simulations to avoid erroneous inferences on the system.

Often mean and error bars of the weekly variable generation costs are reported for analysis. Mean costs for each of the 12 simulated weeks $w \in [W]$ are averaged over the number of simulation runs $r \in [R]$:

$$\overline{C}_W^v = \frac{1}{R} \sum_{r=1}^{R} \frac{1}{W} \sum_{w=1}^{W} c^v(G_C^{r,w}), \tag{4.2}$$

where $\overline{C}_W^v$ is the point estimate of the weekly mean variable generation costs of R independent simulation runs. Error bars show the standard error of the weekly variable generation costs indicating the variations between weeks. The standard error (SE) is calculated as:

$$SE_{\overline{C}_W^v} = \frac{1}{\sqrt{W}} \sqrt{\frac{1}{W} \sum_{w=1}^{W} \left(\frac{1}{R} \sum_{r=1}^{R} c^v(G_C^{r,w}) - \overline{C}_W^v \right)^2}. \tag{4.3}$$

The number of required simulation runs can be determined following the guidelines for the analysis of terminating, stochastic simulations by Law (2011). For a detailed description of this procedure and the assessment of replications required for the residential demand model see Appendix C. In the following, if not indicated differently, evaluations are conducted based on five replications of each simulation scenario. This results in an average runtime for the base scenario over 12 weeks of approximately 1.3 hours for an optimization horizon of one day and 4.7 hours for optimization of one week. Note that model extensions (e.g., uncertainty in renewable generation or storage valuation for EVs and stationary batteries) and scenario variations increase runtime for daily optimization up to 6 hours for one simulation run of 12 weeks.

4.4 Optimal Scheduling of Residential Load

The following analysis is based on the assumption that on the operational level an aggregator can directly control residential appliances. A one week optimization horizon has been chosen.[6] This section illustrates the aggregate effects of direct control on load and generation. Further, the behavior of flexible residential loads is illustrated and described in more detail.

4.4.1 Demand & Supply Behavior

The results with static household loads and uncoordinated charging are presented to illustrate the benefits of demand flexibility of residential loads. In the upper part of Figure 4.3 one example week of static load (Static) is illustrated in the right panel and the corresponding renewable and conventional generation in the left panel. Base load shows typical patterns according to the standardized load profiles. Load of flexible household appliances hardly differ between weeks due to the large population. Given the repetition of weekly driving profiles, EV load remains identical over all weeks for uncoordinated charging.

[6] This choice is driven by previous work on EV charging where typically an optimal charging problem as a linear program is formulated with full information over one week (Flath et al., 2013; Schuller et al., 2014).

The aggregate load curve shows distinct morning and evening peaks. In these peaks EV charging loads ad to a high base load and the usage of other—potentially—flexible appliances. At weekends the morning peak appears some hours later as compared to work days. In the renewable generation pattern high midday PV peaks can be observed. Beyond these peaks conventional generation is required at almost all times. In this example week 60.6 % of the static load can be supplied by wind and PV generation. To cover the highest peak load in the evenings maximum conventional generation requirements exceed 420 kW.

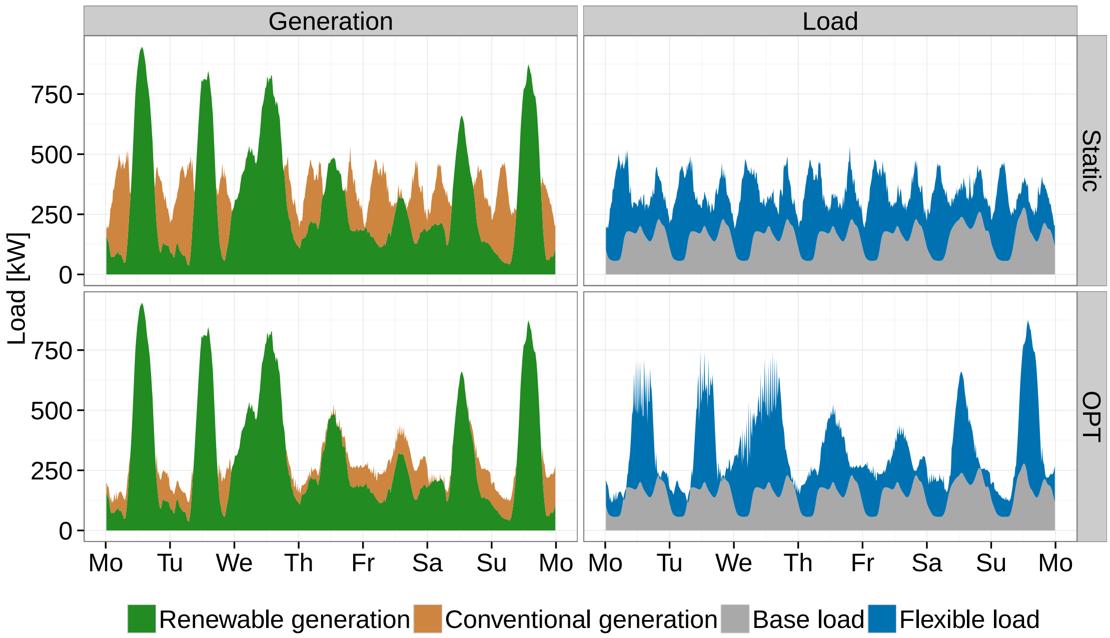


Figure 4.3: Illustration of load and generation behavior

The ability to compensate fluctuations of renewable power supply is demonstrated in the bottom right panel. Applying direct load control, household loads can be scheduled in times with high output of renewable sources. Conventional generation requirements can be reduced as depicted in the bottom left panel. For the example week 83.9 % of the household appliance and EV charging load can be covered by renewable sources and conventional generation peaks are reduce to 160.9 kW.

4.4.2 Flexible Demand Behavior

A more detailed view on the effects of controlling flexible demand is provided in Figure 4.4 by comparing consumption of static appliances and load under optimal scheduling. For ease of exposition some loads are merged to form appliance groups: The “Cooling”’ group comprises fridge and freezer, “Semi-auto” the appliances washing machine, dishwasher, and dryer, and “Storage” covers storage water and space heaters. EVs and stationary batteries (“Battery”) are considered individually in the analysis. Exemplary load profiles on individual device level are provided in Appendix D. Furthermore, the figure includes the net renewable generation ($G^{RES} - L^{B}$). In the static scenario two peaks in the daily load patterns appear. During night load of storage space and water heaters accumulates, in the evening EV charging ads to the existing peak of household (base) load. During work days EV charging takes place predominantly in the morning and evening after trips to or from work. At weekends, vehicles are more randomly pursued and charging activity is spread out. Under static load regimes load coverage through renewable energy sources occurs only if load and generation patterns match by coincidence (e.g., early Wednesday morning in Figure 4.4).

Under the optimal strategy load peaks occur in times of sufficient renewable generation. This way, renewable generation usage is maximized and required conventional generation reduced. Figure 4.4 shows that storage water and space heater operations are shifted from night to PV peaks at noon. If only moderate PV generation is available (see Friday and Sunday), their load is distributed to avoid load concentrations and thus large conventional generation capacities. The periodic cycling of some appliances, particularly cooling, is an artifact of the optimization, which schedules all operations of one type in the same slot. Charging load of EVs is scheduled to the weekly generation peaks. Given their inter-day flexibility EVs are interesting for scheduling and can largely improve load coverage by renewable energy sources. Stationary batteries are integrated for optimal schedule. In Figure 4.4 it can be seen that they have a small effect. They store electricity at the end of periods with high availability of renewable generation and discharge at the beginning of low generation periods. Further, battery storages supply electricity in short periods of residual load concentrations. In a power system such a near-term provision of electricity can help to optimize ramping of power plants.

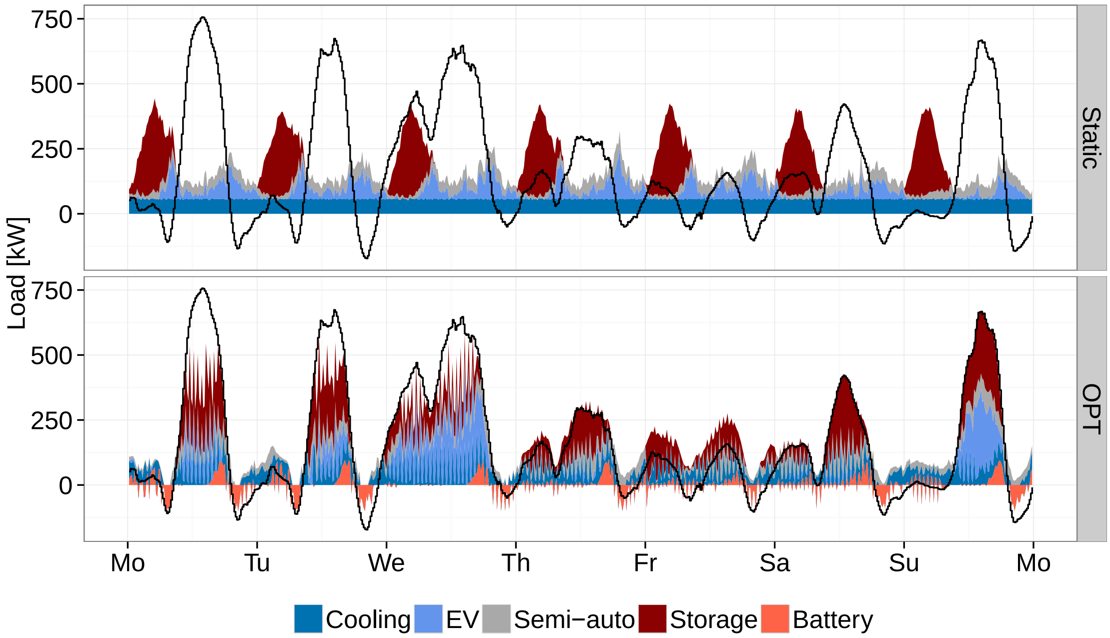


Figure 4.4: Detailed illustration of load behavior and net renewable generation

4.5 Decision Support for Demand Aggregators

Flexible loads affect different decision levels of an aggregator. On the *operational level* flexible devices can be controlled to achieve an improved balancing of demand and supply in the portfolio (Vandael et al., 2011). Efficiency of balancing is largely influenced by forecast quality and optimization lookahead. However, a large amount of flexible consumers is not necessarily enough to guarantee load balancing and thus the composition of the portfolio is important (Petersen et al., 2013). The potential of balancing based on flexible loads largely depends on the right combination of intermittent generation and flexible consumers in the portfolio. Thus, customer portfolio decisions on a *tactical level* are important to achieve improved load balancing as well as long term *strategic investment decisions* in renewable energy sources to determine the composition of the generation portfolio.

For an analysis of balancing potentials the assumption of full information over an entire week is hardly appropriate. In the following, model adaptions to enable day-ahead balancing with limited information are discussed. Then, the base scenario of the integrated model is applied to assess the cost reduction potentials flexible demand can provide for an aggregator on operation level. Further, effects of different demand (tactical) and supply (strategic) compositions in portfolios on load coverage through renewable sources are analyzed.

4.5.1 Information Availability

The analysis of optimal scheduling under full information has only limited practical relevance (Flath et al., 2013). To facilitate a more realistic day-ahead balancing, model alterations that enable daily optimization are presented. Particularly, the EV charging and battery storage models call for an adaption to retain intra-day flexibility. Furthermore, the integration of uncertainty in PV and wind generation is illustrated and its effects are discussed. The results from the weekly optimization provide an upper bound for the alternative settings.

Daily Optimization

Reducing the optimization horizon to enable day-ahead balancing is simple for the residential household appliances. The representations of fridge, freezer, storage water heater, and storage space heater do not require any changes. To introduce flexibility in the operation of dishwasher, washing machines, and dryers a latest feasible finishing time is randomly selected. For some operations this finishing time might pass the end of a day. In these situations the flexibility interval for semi-automatic appliances is cut and their operation has to finish at that day. Hence, shifting to night hours of the following day is not possible and DR potentials of these appliances might be slightly underestimated.

EVs and stationary batteries possess inter-day flexibility. Requiring the same level for initial and terminal SOC (see Conditions 3.14 and 3.19) impedes this flexibility for daily optimization horizons. However, with a shorter horizon the need to store energy at times of excess generation for a future purpose may be even more important. Therefore, following Scott et al. (2013) a value for the left-over electricity θ at the end of the optimization horizon is introduced. The resulting objective function including storage valuation is given by

$$\min_{G_C,x,\phi} \sum_{t=1}^{T} c^v \left(G_C^t\right) - \theta_v \sum_{v \in \mathcal{V}} \overline{b}_v \psi_v^T - \theta_s \sum_{s \in \mathcal{S}} \overline{b}_s \psi_s^T. \tag{4.4}$$

For the storage value an arbitrary low number is chosen ($\theta = 0.01$). This, incentives charging in hours with excess electricity from renewable energy sources with zero variable costs. At the same time, this low storage value avoids charging from conventional generation for EVs and enables discharging from stationary batteries in times of excess load.

With the reduced optimization horizon some trips might become infeasible, e.g., an EV user departing early in the morning for a long trip. Particularly, in periods of low renewable generation EVs postpone charging. The resulting low SOC levels increase the number of infeasible profiles. Thus, shorter optimization horizons call for a minimum SOC constraint to prevent infeasible EV profiles (see Equation 3.21). Figure 4.5 shows weekly SOC trajectories of 10 EVs for different optimization horizons as well as the impact of the integrated storage valuation. The figure depicts the same example week as before with a generation peak on Wednesday (see Figure 4.3). For an optimization horizon of one week EV charging takes place in renewable generation peaks especially on Wednesday. Initial and terminal SOC levels are identical.

The mid panel depicts the reduced flexibility in charging when the same initial and terminal SOCs are applied for single day optimization. In this setting charging takes place at the daily generation peaks. Yet, inter-day flexibility is lost and high generation days during the week can not be fully utilized. Storage valuation allows to recapture flexibility in EV charging. In the example week EVs can exploit the renewable generation peak on Wednesday and fully charge their batteries (see right panel of the figure). At times when less renewable generation is available (Friday to Saturday), EVs only charge when needed for a trip resulting in lower SOC levels. In low generation periods also the effect of the minimum SOC constraint can be observed. Despite low availability of renewable generation, one EV charges its battery on Friday to reach the minimum SOC share of 0.3. Concurrently, it can be observed that EVs start with full batteries due to excess renewable generation

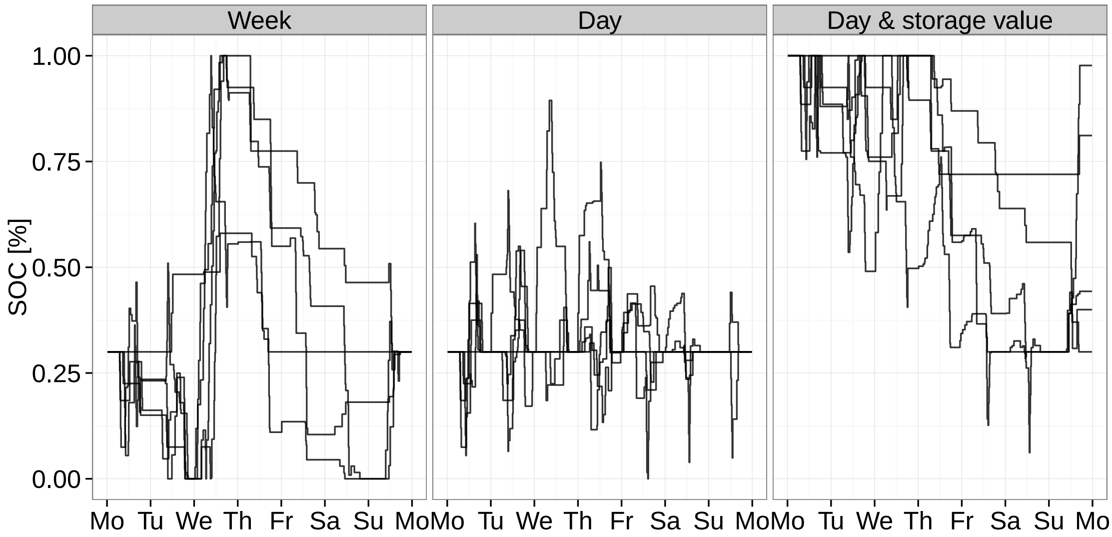


Figure 4.5: SOC level evolution for different optimization horizons

the week before. Thus, storage valuation retains inter-day flexibility but also allows inter-week flexibility of EV charging.

Uncertainty

For day-ahead scheduling of residential devices renewable generation is not exactly known in advance. Yet, day-ahead forecasts for PV and wind output are available and can be integrated into the simulation. Obviously, uncertainty in PV and wind generation leads to higher costs for the aggregator as generation tracking will be less precise and the usage of conventional generation increases. The example week in Figure 4.6 depicts how uncertainty increases the usage of conventional generation. With high renewable generation, e.g., midday PV peaks, forecast errors do not affect conventional generation needs as the residential loads can not make use of the available generation. A different situation arises during hours with low generation of renewable energy sources, such as Friday noon. Here, load is scheduled to make use of the forecasted renewable generation. Nevertheless, the real generation is much lower and residential load largely exceeds renewable generation. A more detailed analysis of decreasing system efficiency due to uncertainty is given in the following section.

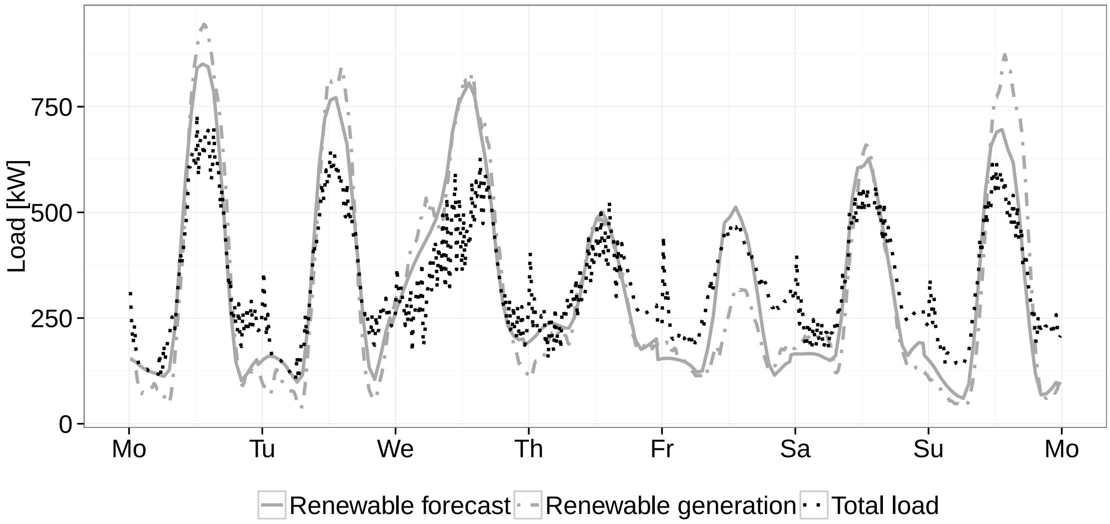


Figure 4.6: Effect of uncertainty in renewable generation

4.5.2 Operational Level

On the operational level an aggregator can control household appliances, EV charging and stationary batteries to achieve a more efficient matching of demand and supply. The potentials of direct load control for day-ahead balancing on the operational level are analyzed in the following. To this end, a system with centralized load control is compared to one with static demand. Under direct load control two different optimization horizons, uncertainty in renewable generation, and the effect of the storage valuation constraint are investigated. Remember the two sub-objectives for a cost-aware coordination of flexible loads which entail reducing total conventional generation usage and peaks of residual load. The two components are first analyzed individually. Subsequently, variable generation costs serve to integrate these two dimensions.

Table 4.2 shows maximum residential loads, capacity requirements for conventional generation, and load coverage by renewable generation under different scenarios. Starting with the uncoordinated scenario (Static) the table includes direct load control for optimization horizons of one week (OPT Week) and one day (OPT Day) with full knowledge of renewable generation and the same levels for initial and terminal SOCs for EVs and stationary batteries. Furthermore, storage valuation (OPT

Day Storage Value) and uncertainty in future renewable generation (OPT Day Uncertainty) for daily optimization are shown. Maximum values and quantiles in the table represent the worst cases. Load coverage through renewable generation is the estimated mean value over all runs.

Table 4.2: Load peaks, maximum conventional generation (CG) requirements and average load coverage through renewable generation

	Load peak		CG		Load coverage
Scenario	Max [kW]	Quantile [99.5%]	Max [kW]	Quantile [99.5%]	Average [share]
Static	705	86.3	682	31.7	0.63
OPT Week	1234	86.3	320	15.2	0.82
OPT Day	1006	86.3	360	18	0.79
OPT Day Storage Value	1170	86.7	360	15.6	0.82
OPT Day Uncertainty	1086	86.7	536	18	0.79

The load concentration results indicate that centralized control increases maximum load values. Without load control household appliances and EV charging loads are randomly distributed and their aggregated load does not show high concentrations. In contrast, the static demand scenario shows higher capacity requirements for conventional generation. Without coordination, demand will match generation from volatile sources only by chance. If load does not match generation, high conventional capacity requirements can be the consequence. Under a direct load control regime devices can be scheduled in hours of high renewable generation without any costs.[7] Thus, load control can reduce conventional generation capacity requirements by almost 50 %. Weekly optimization under full information establishes minimum values for conventional generation capacity. Yet, under uncertainty in renewable generation conventional generation capacity required remains at a high level similar to uncoordinated charging. At times where a high renewable generation output is predicted, also, a large amount of load might be scheduled. If high predictions for renewable generation do not materialize, the schedule with deliberately concentrated loads has to be supplied by conventional generation (Figure 4.6 provides an example

[7] Note that grid capacity constraints are not included in the model and might put additional limitations on load concentrations in scheduling. However, such constraints can easily be integrated in the dispatch model.

for this effect). Looking at the conventional generation quantiles reveals that high capacity needs for the uncertainty scenario only occur in very few times as the 99.5 % quantile has a similar level compared to the remaining scenarios with load control. This observation indicates that high forecast errors do not occur often.

Looking at the amount of renewable generation utilized it can be seen that without DR only 63.2 % of the load can be covered by available wind and PV generation. This value is about 17 % lower than the load coverage under optimal scheduling. Reducing the optimization horizon with fixed initial and terminal SOCs for EVs and stationary batteries comes along with less load coverage. Storage valuation gains back the intra-day flexibility and increases the coverage level again. Even under uncertainty the storage valuation feature in the model leads to a high load coverage level.

The stylized power system model reflects both variable generation costs and capacity costs. To this end, the model includes costs for total amounts but also penalizes high values of conventional generation. In Figure 4.7 variable generation costs are depicted. Costs are normalized to the static scenario without DR. Irrespective the model specifications, direct load control greatly reduces variable generation costs as compared to a system with uncontrolled residential household loads. At first glance this large costs decrease might be astonishing looking at the lower increase in load coverage by renewable energy sources. However, variable generation costs entail total amount *and* peaks of conventional generation. High maximum conventional generation requirements and also the high 99.5% quantile shown in Table 4.2 support the conclusion that conventional generation peaks are the cost drivers. Looking at the error bars it can be observed that load control also reduces weekly variance in variable generation costs. Still, between individual weeks large cost differences can be observed.

Looking at the scenarios with load control, obviously, the lowest costs are achieved with the optimization horizon of one week. With a shorter horizon the same initial and terminal SOC for EVs and stationary batteries impedes inter-day flexibility and increases costs. Taking into account the value of left-over electricity at the end of the optimization horizon costs can almost be reduced to the level of the full week optimization. Therefore, Objective Function 4.4 including storage valuation is

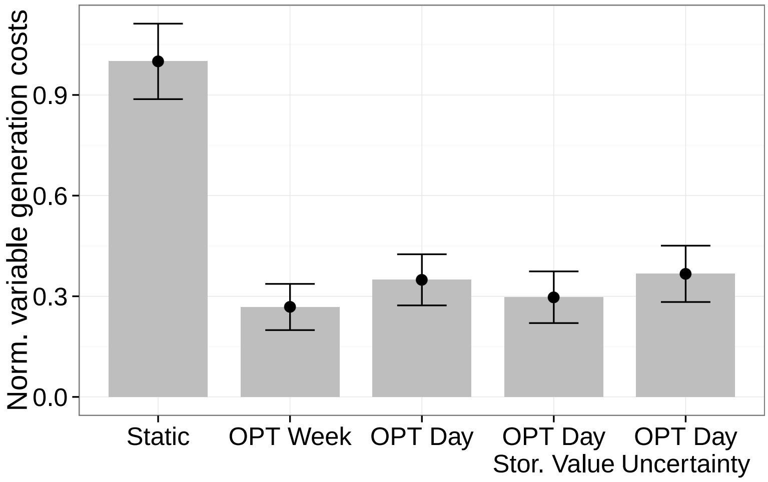


Figure 4.7: Variable generation costs for different settings

applied for subsequent evaluations and the Constraints 3.14 and 3.19 setting initial and terminal SOC to a common level are dropped.

Uncertainty in renewable generation results in the highest costs among the centralized control scenarios. Compared to the daily optimization with full knowledge costs increase in average about 7 %.

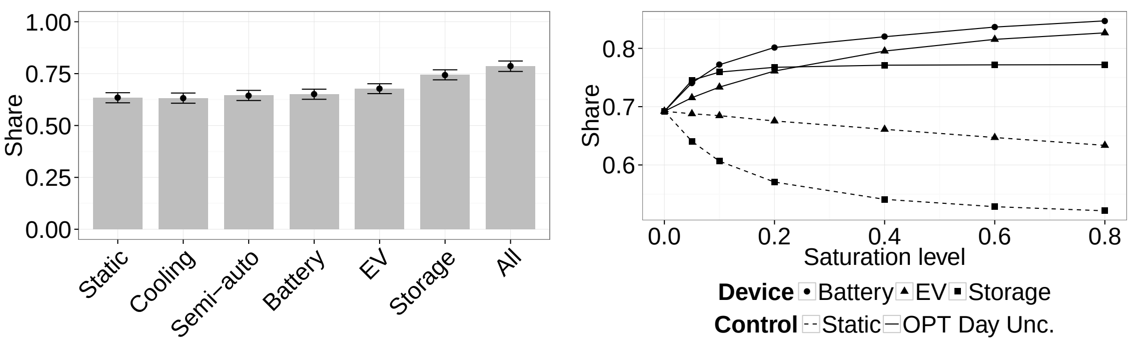
4.5.3 Tactical and Strategic Level

In the medium term an aggregator can decide on the portfolio of flexible customers (tactical) and in the long term on the portfolio of intermittent generation (strategic). Demand and supply portfolio composition largely influences balancing potentials. On the demand side drivers for these potentials are appliance types available for load control and the adoption level of these appliances in the population. On the supply side the main drivers are installed capacity and type of intermittent sources (wind or PV). The following evaluation shows the effects of the drivers on demand and supply side on load coverage through renewable generation and conventional generation requirements. In addition, variable generation costs are analyzed to assess overall system efficiency.

Tactical - Availability of Flexible Demand

On the demand side devices for load control and their availability in the portfolio are the main sources of the flexibility available to an aggregator. To evaluate load coverage through renewable generation for the potentially flexible devices in a residential area they are investigated separately and only one device group is assumed to be controllable for this analysis.

Results for the simulations of direct load control under uncertainty are shown in Figure 4.8a. Scheduling of cooling appliances, such as refrigerators and freezers, does not improve the load coverage by renewable generation as compared to the static scenario and the coverage level remains constant at 63.3 %. The small flexibility interval of fridge and freezer impedes a shift to high RES generation hours. A marginal increase can be observed for the semi-automatically controlled appliances. Direct load control of dishwashers, washing machines, and dryers results in an average coverage level of 64.4 %. Despite their small availability in the base scenario stationary batteries lead to load coverage through renewable generation of 65.1 %. The highest improvements can be reached through control of stationary batteries, EVs, and storage heaters. Weekly variations of load coverage have a similar range for all device groups.



(a) Single devices flexible (b) Varying saturation levels of large loads

Figure 4.8: Average load coverage through renewable generation for different demand scenarios

Apparently, the penetration level of the devices largely influences the potentials of each group. As stationary batteries, EVs, and storage heaters have the largest contribution for increasing the load coverage by electricity from renewable energy sources, these appliances are selected for an analysis in more detail. Figure 4.8b depicts the load coverage results for different penetration levels of these appliances. At a penetration of zero only base load, cooling, and semi-automatically controlled appliances are included and DR is not applied. Based on this scenario, subsequently, the availability of batteries, EVs or storage heaters is increased. In the absence of load control storage heaters are distributed during night hours and a decrease of load coverage by renewable generation can be observed even for low penetration levels. In contrast, EV charging is spread over the whole day and can make use of PV generation. Thus, higher EV shares result only in a slight decrease of load coverage by renewable generation.

Under load control even small shares of batteries, EVs or storage heaters can improve load coverage. The latter have a high daily consumption and are modeled as completely flexible within one day, thus, explaining the steep increase of load coverage for low penetrations. Yet, above 10 % penetration only marginal improvements can be achieved with storage heaters as daily operation patterns limit their flexibility. In the work at hand stationary batteries are much smaller units. Due to their ability to feed electricity back to the grid and their inter-day flexibility, they outperform storage heaters at penetration levels above 10 %. EVs show a similar behavior as stationary batteries but due to reduced availability and missing ability of feeding-back they perform somewhat worse.

For an analysis of the conventional generation requirements duration curves for residual load of one example simulation run are depicted in Figure 4.9. Remember that residual load describes residential demand exceeding renewable generation. It can be observed that control of cooling and semi-automatically controllable appliances hardly changes residual load. Stationary batteries can decrease residual load in some hours but at the low availability levels do not affect the maximum load value. In addition to their potentials for increasing load coverage through renewable generation, EVs and storage heaters also reduce the maximum residual load and thus the required conventional generation capacity.

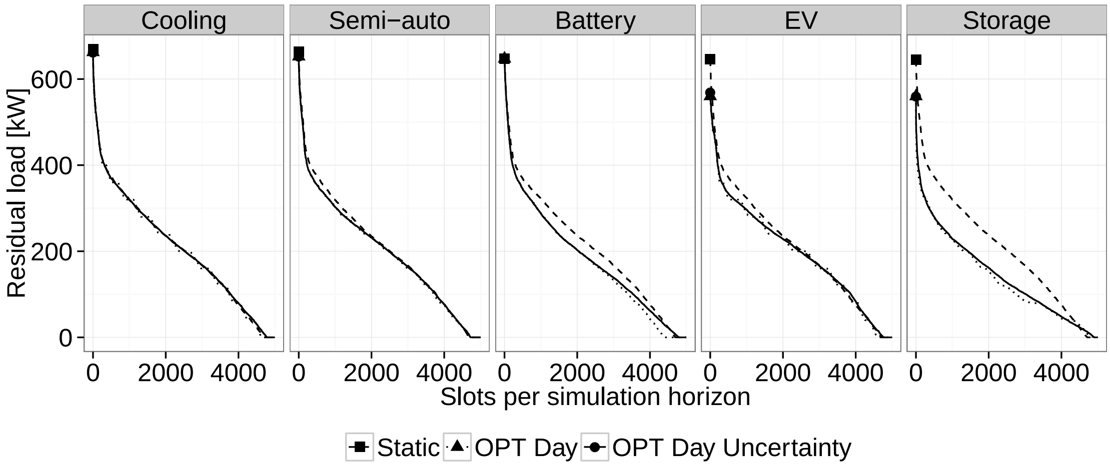
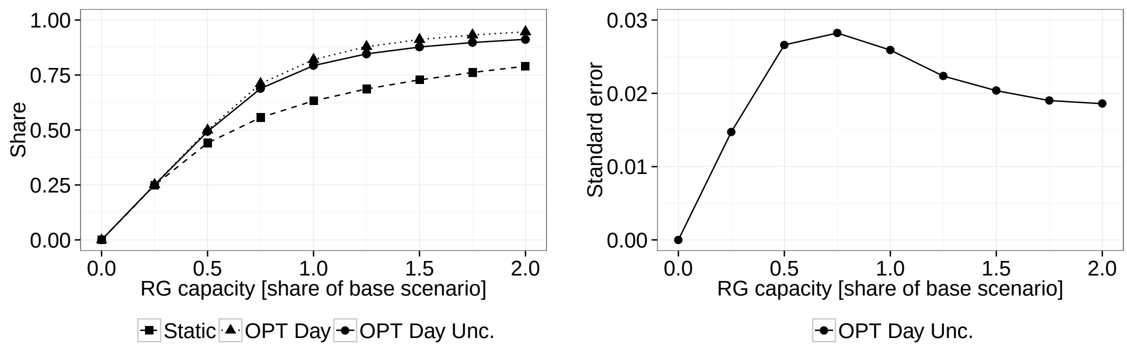


Figure 4.9: Residual load duration curves for different demand scenarios (Simulation horizon $T = 8064$ slots)

Strategic - Installed Renewable Generation Capacity

In the base scenario a power system with a high installed capacity of intermittent renewable energy sources is assumed. To this end, empirical wind and PV generation data is scaled to match total consumption of the demand side over the simulation period. Clearly, the installed capacity of wind and PV has a large influence on the load share covered through renewable generation. For a better understanding of renewable generation capacities, wind and PV data is scaled to match different levels of total demand. Thus, they are representing generation portfolios with different shares of wind and PV installations.

The left panel of Figure 4.10 shows the average weekly coverage of load through renewable generation for portfolios with different wind and PV capacities. If the installed generation capacity is small, control of flexible demand does not increase coverage. When the capacity of renewable sources could theoretically cover 25 % of total load, direct load control starts to improve load coverage slightly above the static scenario. At higher generation capacities, the benefits of load control become more pronounced as the gap between controlled and uncontrolled load widens. However, if installed capacity increases further the gains of load control start to diminish. Uncertainty in the output of wind and PV reduces load coverage. The gap between load control under full information and uncertainty is also increasing in the installed capacity.



(a) Average load coverage (b) Variation of weekly load coverage

Figure 4.10: Load share covered for different levels of renewable generation capacity

Output of renewable generators largely differs between weeks. The simulation results show that at a capacity which could cover 75 % of the system load weekly load coverage ranges from 54.5 % up to 82.9 %. For the maximum capacity analyzed the variation in weekly coverage ranges from 75.9 % to 99 %. The right panel of Figure 4.10 illustrates variations of weekly load coverage for different levels of renewable generation capacities using the standard error. With a low installed capacity individual weeks do not show a great variation of load coverage. When the benefits of load control emerge, the weekly differences also become more apparent.

For an analysis of the conventional generation requirements duration curves for residual load of one example simulation run are depicted in Figure 4.11. The load duration curves show that an increasing renewable generation capacity reduces the number of hours in which conventional generation is required. Furthermore, it can be observed that load control can often reduce residual load levels. Under full information the shape of the residual load with load control, allows to identify the steps of the variable generation cost function. If possible, the optimization avoids to schedule load beyond breakpoints of the piecewise linear function. This results in residual load being concentrated below breakpoints. Uncertainty smooths out these load concentrations.

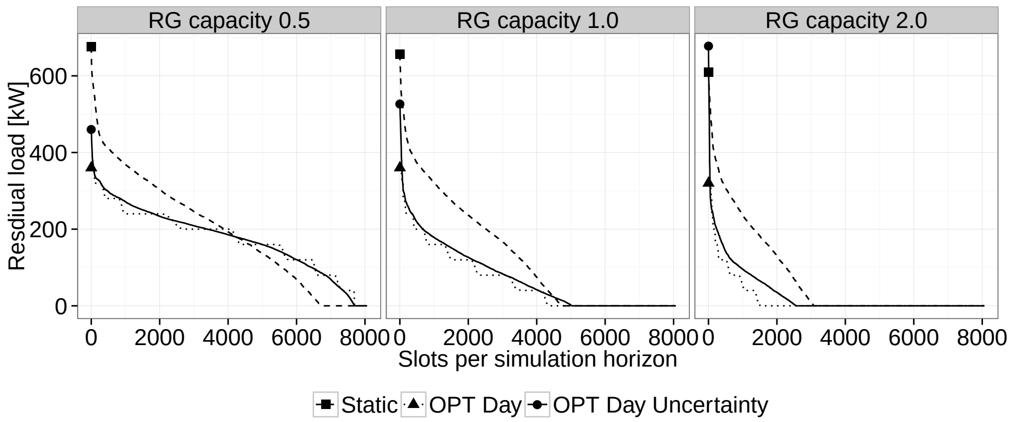


Figure 4.11: Residual load duration curves for different installed renewable generation capacities (Simulation horizon $T = 8064$ slots)

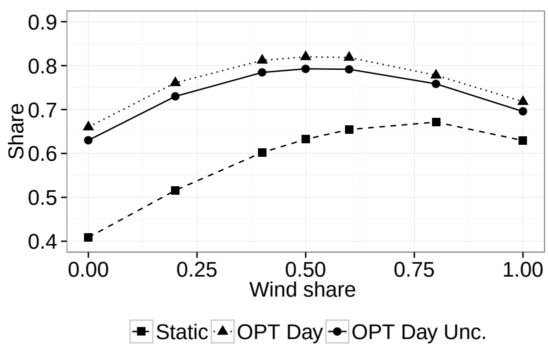
In the absence of load control increasing renewable generation capacity does hardly influence the maximum residual load level. Thus, maximum conventional generation capacity requirements remain at a high level. Load control under full information greatly reduces maximum load values already at low installed renewable generation capacities. With higher capacities the maximum values can only be reduced slightly more. Under uncertainty the load duration curve with direct load control has a similar shape as under full information. However, looking at the maximum residual load values a gap between load control under full information and uncertainty can be observed. This gap increases with larger renewable capacities. In the right panel the maximum residual load under uncertainty even passes the static scenario. With higher renewable capacities also the forecast errors augments. Devices scheduled in such an erroneous forecasted generation hour can lead to large residual loads.

Strategic - Share of Intermittent Sources

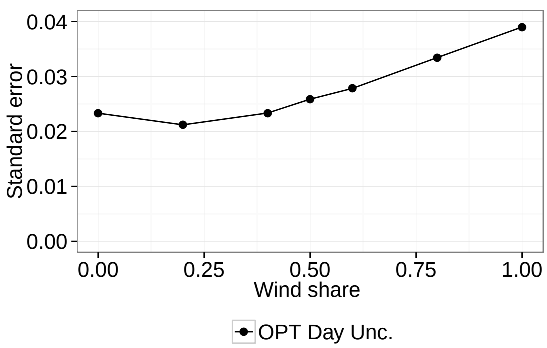
So far an equally balanced generation portfolio of wind and PV has been analyzed. Yet, the different output profiles of wind and PV call for an assessment of varying shares of the two generation types in the portfolio. The left panel of Figure 4.12 illustrates load coverage through renewable generation for various portfolio mixes of intermittent sources. A wind share of zero corresponds here to a PV-only portfolio.

For both, coordinated and uncoordinated load, a PV portfolio has a lower load coverage than a wind-only portfolio. A mixed portfolio improves load coverage by renewable generation. Considering the volatile output in pure PV or wind portfolios, high generation hours cannot be exploited effectively, while in a mixed portfolio the two sources complement each other. Under load control the best coverage can be reached with equally mixed PV and wind. In a regime without load control a wind dominated portfolio leads to improved load coverage. This is not surprising as PV generation is concentrated during few hours while, wind generation is more distributed over the day. Thus, uncontrolled load of the residential area is more often matched by coincidence. This also means that DR offers the largest benefits in PV portfolios.

The intermittent characteristic of renewable generation influence their ability to cover load. In the simulation wind as sole generation source achieves weekly coverage from 42.3 % to 78 %, for a PV portfolio the range is 45 % to 73 %. The right panel of Figure 4.12 illustrates the variation of weekly load coverage for different renewable generation capacity levels using the standard error. It can be observed that a wind portfolio leads to a higher coverage by renewable energy sources as a PV portfolio; but, wind shows larger weekly variations.



(a) Average load coverage



(b) Variation of weekly load coverage

Figure 4.12: Load share covered for different shares of wind and PV in the portfolio

The duration curves in Figure 4.13 show the highest number of slots without any residual load for an equal mix of wind and PV. For a portfolio dominated by either source conventional generation is more often required. Again, the large residual load reduction due to DR in a PV portfolio is visible. With increasing wind shares these benefits decline. Further, the figure shows that without load control maximum residual load is hardly influenced by wind and PV shares. The three portfolios included in the figure have very similar maximum values for static demand. Under full information, centralized load control can greatly decrease peaks and thus reduce required conventional generation capacity. Similar to the static scenario, the maximum residual load remains fairly constant over the three portfolio mixes. Yet, under uncertainty larger maximum values occur in a PV dominated portfolio. Due to the higher forecast errors for PV generation, this portfolio requires the same conventional generation capacity as uncontrolled load (see Figure 3.9). In such an unfavorable situation, load is scheduled to make use of a PV peak. Nevertheless, real generation is much lower and largely exceeds PV generation. In a wind portfolio the maximum value declines and reaches almost the level of optimization under full information.

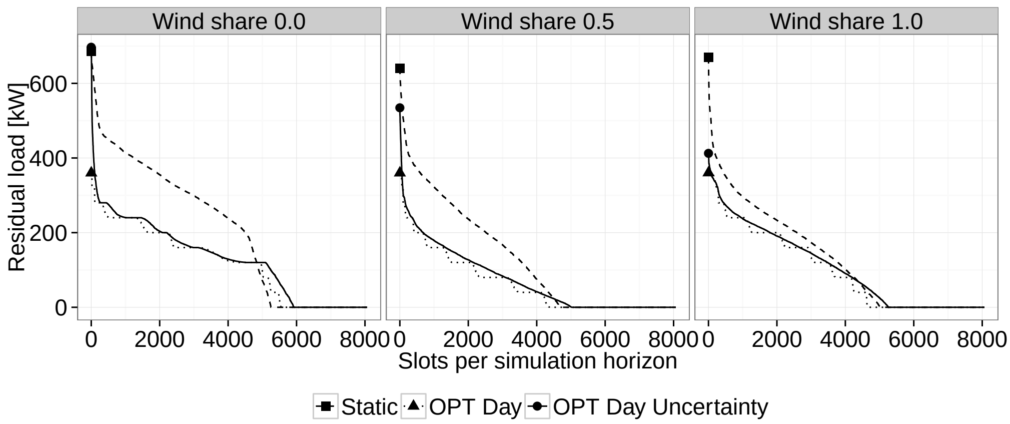


Figure 4.13: Residual load duration curves for different wind and PV shares (Simulation horizon $T = 8064$ slots)

For a comprehensive assessment of demand and supply side sensitivities for an aggregator the analysis has to be extended beyond load coverage through renewable generation and the effects on the overall system have to be looked at.

Overview - Variable Generation Costs

In order to analyze the impact of flexible residential load on the aggregate system for different demand and supply settings, the stylized power system model is used. The application of this model allows to report variable generation costs integrating both, total usage *and* peaks of conventional generation. Figure 4.14 illustrates the variable generation costs for the demand and supply settings described before. All values are normalized to the base scenario without load control. Instantly, the cost decline due to load control can be seen in all three panels. Uncertainty in renewable generation slightly increases costs as compared to load control under full information. On the demand side larger loads such as batteries, EVs and storage heaters can be identified as the most promising options for load control in the applied portfolio (see left panel). Cooling and semi-automatically controlled appliances have fairly low impact on variable generation costs. High renewable generation capacities decrease variable generation costs, though, when a share of 0.75 of total load can be covered by renewable generation cost reduction starts to flatten(middle panel).[8] In the right panel it can be observed that a balanced portfolio results in the lowest variable generation costs. The more one source is dominating the portfolio the higher costs become.

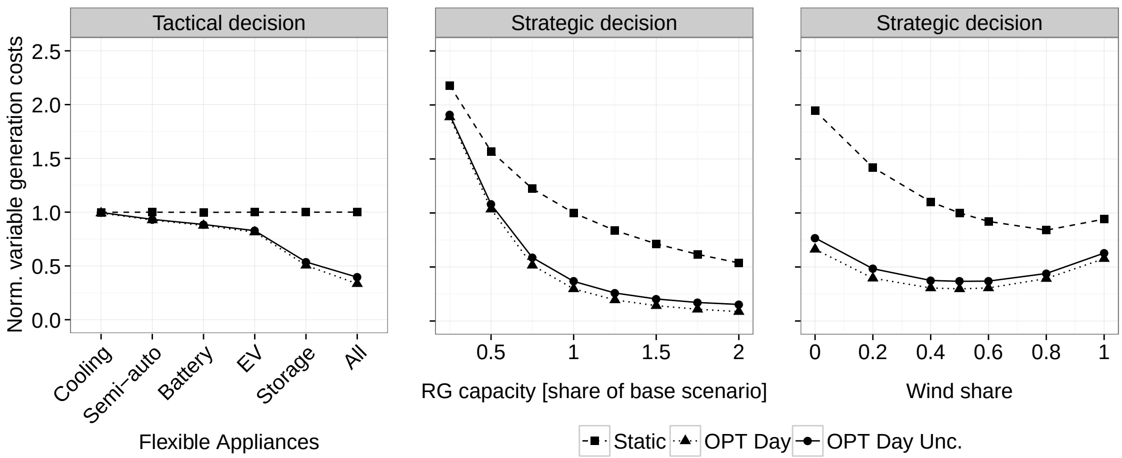


Figure 4.14: Variable generation costs for various supply and demand settings

[8]Due to initial investments benefits of addition renewable generation capacities diminish for higher renewable generation capacities.

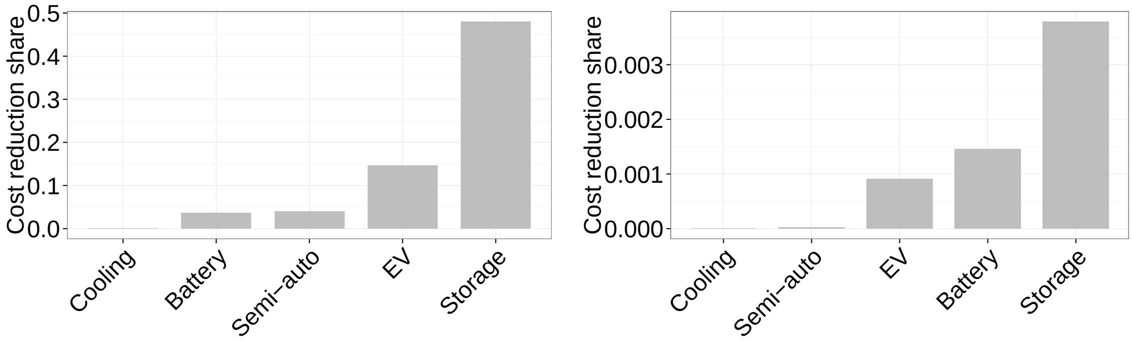
4.6 Opportunities for Residential Households

Scheduling of flexible loads minimizes the costs for additional generation required. Improved system efficiency can be passed on to residential households and lower their electricity expenses. However, there are instant winners and losers among customers when introducing DR (Faruqui, 2010). For providing flexibility to the aggregator residential households should receive some form of incentive payments (Albadi and El-Saadany, 2008). Flexible customers can expect a higher compensation and thus lower electricity costs compared to customers with no or low flexibility. In the following, the demand and supply model is applied to estimate the value of individual devices for DR. On this basis customers benefiting from DR programs can be identified. Then, the results on household appliances are used to determine the key dimensions of flexibility in a smart grid and to prioritize flexible loads for DR applications.

4.6.1 Demand Response Winners

An integrated scheduling of all appliances under full information is executed to identify customers profiting from demand response. Then, variable generation cost changes between static and responsive demand are calculated and mapped to the operation of devices.

Figure 4.15a depicts the share of variable generation cost reductions for the known device groups applying the integrated optimization. It can be observed that cooling appliances despite their high availability hardly contribute to system efficiency. EVs and particularly storage heaters show the highest cost reduction potentials in the population. Interestingly, stationary batteries and semi-automatically controlled appliances have almost the same reduction potential. Stationary batteries can be classified as more flexible as washing machines, dishwashers and dryers, but in the population batteries have a much smaller share. DR benefits for individual household customers depend on their appliance set. Thus, to identify demand response winners among household customers reductions by individual appliances have to be looked at.



(a) Device groups in the population (b) Average device per group

Figure 4.15: Share on variable generation cost reductions

Figure 4.15b includes the average reduction share per device of a group. Three observations can be made in this figure. First, a dishwasher, washing machine or dryer (Group "Semi-auto") provides only marginal potentials for cost reductions in the system and so for the customer to lower his or her electricity bill. Second, scheduling one stationary battery contributes more than a semi-automatically controlled appliance or an EV. Finally, storage heaters show the largest potential. This leads to the conclusion that residential customers can benefit more from demand response when their set of devices includes the EVs, stationary batteries, or storage heaters which contribute in a larger amount to the variable generation cost savings. Note that due to overall improved system efficiency even customers with low flexibility might be better off under general adaption of demand response programs.

Devices showing both, high cost reduction shares in the population and on individual level are the most promising for load control. The former indicates cost reduction potential in the system for an aggregator or utility. The latter facilitates incentive payments to enable customer participation in a DR program.

4.6.2 Key Characteristics of Flexible Demand

Given the share of individual appliances on variable generation cost reductions, it remains an open question what the drivers are that influence the performance of a device with respect to demand response. This first gives rise to the question what characterizes load flexibility and thus the capacity to adapt of a device?

Petersen et al. (2013) provide a taxonomy for modeling flexibility in smart grids. They describe flexible systems focusing on their constraints: power capacity, energy capacity, energy level at a specific deadline and minimum runtime. They introduce the term *quality of flexibility* to describe the restrictions (constraints) of a device. However, they state that "better quality means less restricted, not necessarily more flexible". The reason for this differentiation is that the flexibility of a device is determined by the constraints *and* by the specific parameter values of a device. To illustrate this distinction devices of the residential household model can provide an example. Cooling devices are only power and energy constrained. Due to this low number of restrictions they have a high quality of flexibility. EVs are more restricted as they require an additional constraint to reach a certain energy level at a deadline. Yet, controlling large EV loads reduces system costs to a greater extent than control of fridges or freezers.

In the modeling chapter load, operation frequency and shifting distance have been applied to describe relevant technical characteristics of an appliance for DR (see Table 3.3). These appliance specific parameters combined with the quality of flexibility specify DR flexibility of a device. Given these characteristics, the question arises what is the key driver for load flexibility?

To assess the impact of the different flexibility characteristics, Figure 4.16 combines quality (of flexibility), shifting distance, and weekly consumption[9] and maps them on the average savings provided through the devices. Not surprisingly, the largest cost reductions correspond with a high quality (of flexibility), a high consumption and a large shifting distance as shown by the storage heating appliances. Stationary batteries have lower cost reduction potentials due to their lower consumption.[10] EVs have a similar weekly consumption as stationary batteries but a slightly lower shifting distance and a lower quality of flexibility. The importance of shifting distance and consumption for load flexibility can be identified by comparing storage heaters and cooling devices. Both have the same quality of flexibility, but a storage heater can reduce variable generation costs to a much larger extend due to its high electricity consumption and shifting distance. Based on these observations

[9]To facilitate a graphical illustration load during operation and operation frequency are summarized to weekly consumption.

[10]For stationary batteries consumption is calculated as the average weekly charging amount.

it can be seen that the quality of flexibility describing the restrictions of a device is dominated by shifting distance and energy consumption. The latter are the drivers for the *capacity to adapt* of a device.

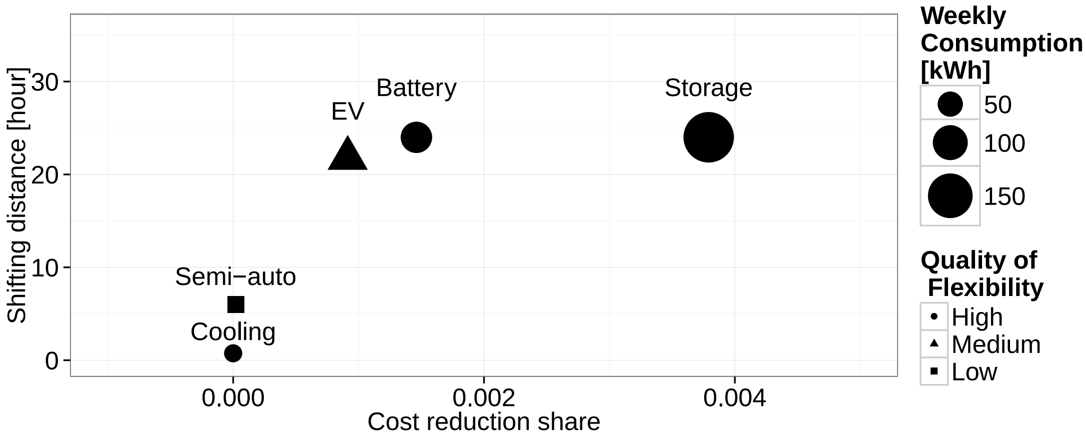


Figure 4.16: Quality of flexibility, shifting distance and consumption determine flexibility and cost reduction potentials of a device

4.7 Discussion

Demand response is a promising approach to facilitate an efficient integration of volatile renewable sources into the power grid. Due to the high costs of real-world experiments, simulations are an important tool to investigate system effects of DR. This chapter presented an integrated demand scheduling and generation dispatch model to estimate DR potentials of direct load control. The model is applied to estimate reductions in variable generation costs in a system with a large share of renewable generation where an aggregator can control loads of various small devices in a residential area.

Load control affects decisions of an aggregator on the operational, tactical and strategic level. The analysis on operational level shows that direct load control can increase load coverage through wind and PV generation and reduce variable generation costs by more than 50 %. Maximum conventional generation requirements can hardly be reduced if uncertainty is considered. This illustrates the need for improved forecasts or real-time adaption of (some) loads to improve the capacity credit[11] of renewable generation (Skea et al., 2007).

An aggregator can decide on demand and supply composition in the portfolio. For demand portfolio planing (tactical level) the results show that batteries, EVs, and storage heaters are the most promising devices for DR in a residential area. In the analysis presented cooling appliances hardly contribute to system efficiency. Yet, for balancing short term fluctuations a large number of refrigerators and freezers might be well suited (Stadler et al., 2009; Kamper, 2010). On a strategic level it is shown that benefits from load control start to emerge beyond a renewable generation share of 50 % on total load. This is in line with the recent analysis of the International Energy Agency (2014). At lower renewable generation capacities DR can hardly improve load coverage with renewable generation and thus system efficiency. With respect to the generation mix in the portfolio two observations can be made. The analysis firstly shows that the highest load coverage through renewable sources can be achieved with a balanced portfolio of wind and PV, secondly, that maximum conventional generation requirements decrease with wind share in the portfolio. Thus, indicating a higher forecast error for PV generation.

Furthermore, the contribution to variable generation cost reduction of devices is assessed. In this analysis EVs, stationary batteries, and storage heaters are identified as the most promising devices. They feature cost reduction potentials in the system for the aggregator or utility and on individual appliance level they enable incentive payments for customers to participate in a DR program. Finally, characteristics to describe flexibility of devices have been listed. Cost saving potentials of individual appliances for DR serve to identify the key properties for load flexibility. The evaluation results suggest that consumption and shifting distance may be more important than the quality of flexibility (i.e., restrictions for scheduling).

4.7.1 Limitations

For the analysis load is scheduled based on a generation forecast and then system costs are evaluated using the realized output of the renewable sources. Utilization of

[11] Conventional generation capacity that an intermittent generator can replace.

a more sophisticated technique to handle uncertainty may further increase system efficiency. Such techniques can include a limit on the utilization of the predicted generation output to reduce uncovered loads in case of forecast errors. Another option might be to use renewable generation data to assess the dependence of the forecast error on the predicted output level. Then, devices can be scheduled based on samples for the renewable output using, for example, a consensus algorithm (Bent et al., 2012).

Further, power system efficiency gains under a centralized control regime are based on full information of device usage for the following day. Unquestionably, these are benchmark results for DR potentials of residential households. However, for some appliances the full information assumption does not seem farfetched, e.g., for storage water and space heaters home energy management systems can estimate the required electricity consumption based on storage temperature level, ambient temperature prediction and presence of the household members (Allerding, 2014). Yet, for semi-automatically controlled appliances or EVs full knowledge of future usage on a daily horizon is not appropriate. Thus, the integration of demand side uncertainty offers interesting opportunities for future research.[12]

Balancing of demand and supply in a power system with high shares of volatile generation is the example employed in this thesis. This is an important step to better understand opportunities and risks of flexible residential demand, but is at the same time a oversimplification of the system. The underlying physical power grid may pose additional constraints on DR. Therefore, a power flow analysis incorporating losses, line utilization, voltage, and transformer utilization is necessary. A more comprehensive assessment of efficiency and greenhouse gas emissions in the power system could be achieved by incorporating a unit commitment model with detailed data on plant costs and characteristics (Sioshansi and Denholm, 2010; Grünewald et al., 2015). Moreover, some assumptions may warrant closer attention to ensure robust results. The present model considers various flexible devices on the demand side. For the sake of simplicity only one representative example configuration per device is integrated. An analysis of heterogeneous device types and of the key pa-

[12]Living labs with real inhabitants and equipped with energy management systems are a promising candidate to elicit these questions.

rameters influencing demand response potentials of devices may help to obtain more robust simulation results. For example, EV flexibility potential is influenced by the availability of charging spots and charging power. Further, in a future smart grid additional technologies might be available for control on the demand side (e.g., heat pump or air conditioning) but also on the supply side (e.g., combined heat and power) of a residential area and should be included in a generalized model.

4.7.2 Future Opportunities

There are various possible extensions or modifications of the model used for estimating system efficiency of residential DR. My model is currently only appropriate for day-ahead balancing of demand and supply. One alternative could be to extend the day-ahead offline optimization to an online setting with frequent re-optimization for real-time adaptions of the load schedule. By this, reducing the gap between scheduling under full information and uncertainty in renewable generation as frequent re-scheduling of the devices allows an adaption on improved forecasts. The work of Subramanian et al. (2013) or Bent et al. (2012) offer first insights to such real-time scheduling for EVs. It would be interesting to investigate the performance and efficiency heuristic optimization approaches can achieve for scheduling loads of a residential household population. By applying heuristic optimization larger populations may be investigated, simultaneously, more frequent re-optimization for real-time scheduling is possible due to the reduced optimization runtime.

So far, the analysis covers generation differences between distinct weeks and shows the benefits of residential demand for inter- and intra-day flexibility. A simulation horizon of one year enables incorporation of seasonal variations of supply and demand. This way, requirements for long term storage or conventional generation capacities could be estimated giving a more comprehensive assessment of the power system efficiency. Further, applying the model to represent a microgrid of a small residential municipality could be an interesting scenario for centralized control of household loads. This requires a calibration of the model using local data on wind and PV generation.

Finally, the simulation presented is limited to German households and their typical appliances. In many countries penetration rates for cooling and semi-automatically controlled appliances are comparable to Germany, but other countries have very different penetration levels for some devices. In contrast to Germany, Australia, the US, or southern European countries show high penetration levels of promising storage heaters. Other devices have not been included in the model (e.g., air conditioning) due to their low share in German residential households. Similar to storage heaters air conditioning involves thermal storage and posses flexible operation times. Thus, they offer large potentials in countries with higher availability of air conditioning in the residential sector. It might therefore be interesting to evaluate benefits of flexible load in countries with different appliance sets in residential areas.

Chapter 5

Coordination of Residential Loads

A detailed demand and supply model not only improves the ability to analyze flexible load and renewable generation portfolios, it also enables the design and evaluation of appropriate load coordination mechanisms. Dynamic retail electricity rates are a promising option to incentivize changes of customer behavior and improve system efficiency (Borenstein et al., 2002). This holds in particular for households equipped with smart meters and behavioral response of residents. However, for automated DR researchers have been pessimistic with respect to the coordination capabilities of price signals due to the tendency of creating herding or load synchronization effects (Gottwalt et al., 2011; Sioshansi, 2012). Ramchurn et al. (2012) note that [Real-time pricing] "can create unexpected peaks in demand, when all individuals respond to a signal in the same way, and inadvertently synchronize with others". They conclude that "demand-side management technologies that simply rely on reacting to control or price signals will not be enough". This calls for adaptive customer prices dynamically reflecting current grid conditions in the spirit of optimal spot pricing (Schweppe et al., 1988). At the same time, Dütschke and Paetz (2013) point out that customer acceptance will require simple and reliable pricing schemes.

This chapter investigates coordination mechanisms for a large number of small flexible loads in residential areas with a focus on price-based control. To retain a clear focus on coordination, the first part of this chapter uses a simple model with EVs instantiating flexible loads and wind generation as renewable source. Standard rate designs are applied to reproduce load synchronization and analyze the influence of flexible demand shares in the system and different rate characteristics. Further, to address the disparity between customer preferences (stable and reliable price signals) and system requirements (effective load coordination), rate design options to reduce synchronization under exogenously specified electricity rates are explored thereby improving efficiency in a power system with a high share of renewable sources. Exemplary rates and load curves illustrate the load desynchronization approaches power surcharges and group pricing. Then, the stylized generation model is applied for a comprehensive assessment of different coordination mechanisms. To better understand the application of the load desynchronization approaches, they are investigated in more detail to provide design guidelines for implementation.

In the second part of this chapter group pricing is analyzed in a more general simulation setting to derive insights for a greater number of real-world power systems. To this end, the full set of flexible appliances of the bottom-up demand model and two intermittent renewable generation sources (wind and PV) are integrated. Furthermore, the impact of uncertainty in renewable generation under price-based control is investigated. A main focus of this analysis is the comparison of centralized and decentralized coordination under uncertainty. Finally, expected savings of residential household appliances and fairness issues of group pricing are discussed.

The remainder of this Chapter is structured as follows. Section 5.1 provides an overview of prior research on price based DR. In Section 5.2 the model for indirect load control using dynamic electricity pricing is described and Section 5.3 gives the basic settings for the two evaluation scenarios applied. Subsequently, the availability of flexibility in the system and key factors for load synchronization under different standard rate designs (real-time, time-of-use and high-low-pricing) are analyzed in Section 5.4. In Section 5.5 design elements (power surcharges, randomized group rates) to reduce load clustering effects are discussed and a sensitivity analysis to identify important parameters for rate design is presented. Moreover, to get a more comprehensive assessment of the proposed pricing schemes variable power system costs are evaluated. In Section 5.6 group pricing is analyzed in more detail. Therefore, a comprehensive model is applied and the level of available information is reduced. Moreover, system effects of centralized and decentralized control regimes are evaluated. Section 5.7 presents the impacts of dynamic pricing on retail customers and discusses fairness aspects. Finally, Section 5.8 concludes, critically discusses the main implications and presents an outlook for future research.

Core parts of this chapter have been submitted for publication. Namely the Sections 5.1, 5.4.2, and parts of 5.5, 5.7.2 and 5.8 are the basis for the working paper of Flath and Gottwalt (2014).

5.1 Related Work

Decentralized decision regimes have lower computation and communication requirements and can better retain customer incentives and privacy concerns as compared to centralized decision schemes (Vandael et al., 2011).[1] Due to the distributed nature of a decentralized control paradigm, a large scale application requires a careful analysis of the emergent system behavior (Ramchurn et al., 2011). Open-loop and closed-loop are two basic principles for decentralized load control. Figure 5.1 sketches the decision making schemes for these two principles. Open-loop control requires understanding of the system to compute appropriate control signals. For closed-loop control the controlled variable is observed and a feedback loop allows adaption of the signal.

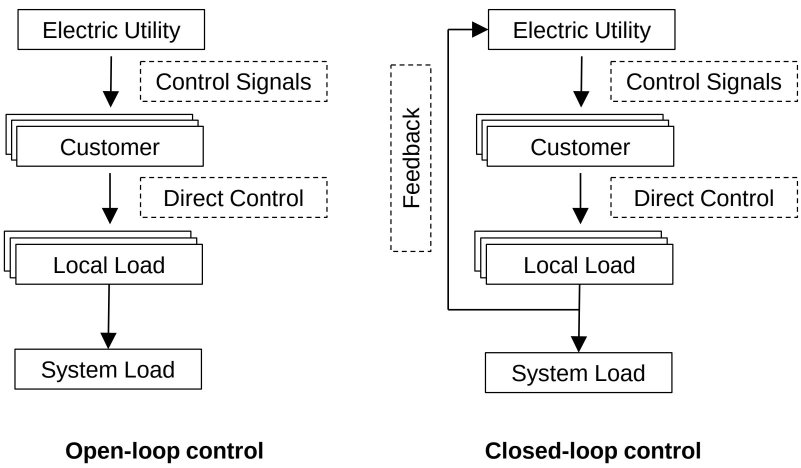


Figure 5.1: Open-loop and closed-loop decision making schemes

[1]This section is incorporated in our working paper Flath and Gottwalt (2014).

5.1.1 Open-loop control

Most commonly, open-loop control in residential DR is instantiated using price-based coordination. This requires some form of dynamic pricing, e.g., TOU pricing, CPP, or RT pricing. Electric utilities carried out various dynamic pricing studies showing that customers are responsive to changes in electricity prices (Faruqui and Palmer, 2012). Grünewald et al. (2015) show that behavioral responses to TOU tariffs reduces overall power system costs in scenarios with high levels of renewable generation. Yet, for automated demand response recent research has been more pessimistic with respect to the benefits of posted price signals due to the tendency of load synchronization (Gottwalt et al., 2011). Furthermore, price-based coordination approaches (TOU, RT) fail to reflect non-convexities of system costs which further decreases their efficiency (Sioshansi, 2012). Other researchers refer to the over-coordination phenomenon as “rebound peaks“ (LeMay et al., 2008; Mishra et al., 2013; Muratori et al., 2014).

5.1.2 Closed-loop Control

Another stream of literature investigates the potential of closed-loop decision making schemes such as market-based or bilateral exchange-based allocation of energy. Mohsenian-Rad et al. (2010) analytically show that such an approach will yield an efficient allocation in a general setting. Using learning agents, Ramchurn et al. (2011) demonstrate that a feedback loop in an RT pricing regime will achieve efficient decentral coordination. Gan et al. (2013) propose an iterative charging control for flexible loads (e.g., EVs) with the aim of filling demand valleys. Based on tentative charging decisions of the EVs the utility adapts electricity prices. Flath et al. (2013) also apply EVs to represent flexible loads in the system. In their work decisions are taken sequentially and thus after the charging decision of an EV dynamic prices are updated according to the new system state. Several authors propose an iterative approach where the electric utility adapts a control signal till a stopping criterion or an equilibrium is reached. The general sequence is as follows: The electric utility generates and broadcasts a control signal to customers. Customers adapt consumption of their shiftable load accordingly and send the changed consumption profile to the utility. The changed profiles are then used to adapt the control signal (Waraich et al., 2013; Wang and de Groot, 2010; Chen et al., 2011; Mohsenian-Rad and Leon-Garcia, 2010).

While these closed-loop approaches may in theory guarantee almost optimal results, a real-world application for retail customers is difficult to implement as it would require forward market activity and expose customers to quantity risk (Bitar and Low, 2012). Consequently, typical RT pricing schemes are posted price schemes where customers receive a fluctuating yet reliable price signal.[2]

5.2 Indirect Load Control Model

Decentralized decision regimes are promising alternatives to centralized control. However, decentralized control paradigms require a detailed analysis of emergent system behavior. The bottom-up residential demand model from Chapter 3 provides a basis to analyze system effects of decentralized coordination mechanisms. Subsequently, an indirect load control model as an instance of decentralized coordination is described. Such a model allows for an evaluation of open- and closed-loop pricing schemes. Further, the simulation process is explained and the computational requirements of a centralized and decentralized control are compared.

5.2.1 Formal Description

Instantiating residential DR using price based coordination leads to a linear cost minimization program, where runs of household appliances, charging of EVs and stationary batteries are scheduled such that the electricity costs are minimized. In contrast to the integrated device scheduling and generation dispatch model for direct load control, scheduling decisions for indirect load control are taken on device level. Thus, after receiving a retail electricity rate $p = [p^1, \ldots, p^T]$ devices individually optimize their execution times by minimizing electricity costs over a time horizon $T \in \mathbb{N}$. In the following, objective functions and constraints for indirect load control

[2]For the sake of clarity, in the following open loop fluctuating prices are referred to as "real-time-pricing", and closed-loop prices as "adaptive pricing".

on device level are presented. For the ease of reading the constraints of the individual appliances are repeated in the following. A detailed description of the devices is provided in Section 3.3.3, for stationary batteries in Section 3.4.2 and for EVs in Section 3.5.3.

Automatically controlled appliances with large loads, e.g., storage water and space heaters are included in set $\mathcal{A}$. The consumption of an active household appliance is denoted by ρ_a and δ_a is the duration of one run. For appliance $a \in \mathcal{A}$ the simulation horizon T is divided in $C_a \in \mathbb{N}$ intervals. For DR runs of appliances are flexible within the respective interval $[s_a^i, e_a^i]$ and the runtimes with minimal costs ($x_a^t = 1$) are selected:

$$\min_x \sum_{t=1}^{T} p_t \cdot \left(x_a^t \rho_a\right) \tag{5.1}$$

subject to:

$$\forall i \in [C_a] : \sum_{t=s_a^i}^{e_a^i} x_a^t = \delta_a. \tag{3.2 revisited}$$

The set $\mathcal{B}$ includes automatically controlled appliances with small loads and frequent operation during one day, i.e., refrigerators and freezers. For these appliances the time horizon T is divided in C_b intervals and runs are flexible within the respective interval $[s_b^i, e_b^i]$. For decentralized load control the operating times ($x_b^t = 1$) of appliance $b \in \mathcal{B}$ per interval are selected by:

$$\min_x \sum_{t=1}^{T} p_t \cdot \left(x_b^t \rho_b\right) \tag{5.2}$$

subject to:

$$\forall i \in [C_b] : \sum_{t=s_b^i}^{e_b^i} x_b^t = 1. \tag{3.4 revisited}$$

Semi-automatically controlled appliances, i.e., washing machine, dishwasher and dryer are comprised in appliance set $\mathcal{C}$. For a run $r \in R_c$ of these appliances $P_r = (\rho_r^1, \ldots, \rho_r^{\delta_r})$ defines the consumption profile. The starting time ($x_c^t = 1$) of one run of appliance $c \in \mathcal{C}$ in the flexibility interval $[t_r^s, t_r^l]$ under indirect load control is determined by:

$$\min_x \sum_{t=1}^{T} p_t \cdot \sum_{k=1}^{t} \left(x_r^k \cdot P_r \left(t + 1 - k \right) \right) \tag{5.3}$$

subject to:

$$\sum_{t=t_r^s}^{t_r^l} x_r^t = 1, \tag{3.8 revisited}$$

$$P_r(\tau) = \begin{cases} \rho_r^\tau, & \tau \in \{1, \ldots, \delta_r\} \\ 0, & \text{otherwise.} \end{cases} \tag{3.10 revisited}$$

The former constraint ensures that each run r starts in the corresponding interval and the latter specifies the load of one run.

The cost-minimizing charging and discharging amounts (ϕ_s) for a stationary battery $s \in \mathcal{S}$ are determined by the means of the following linear optimization problem:

$$\min_\phi \sum_{t=1}^{T} p_t \cdot \phi_s^t \tag{5.4}$$

subject to:

$$\psi_s^t \bar{b}_s = \psi_s^{t-1} \bar{b}_s + \phi_s^t, \tag{3.13 revisited}$$

$$\psi_s^0 = \psi_s^T, \tag{3.14 revisited}$$

where the first constraint guarantees continuity of battery level (ψ_s) and the second avoids discharging at the end of the optimization horizon. Stationary batteries can feed electricity back to the grid. Thus, with charging in low price hours and discharging in high price hours batteries can achieve revenues. Due to the loss free charging process all stationary batteries simultaneously either charge or discharge in every step. To avoid frequent battery activity threatening power system efficiency the vector $A_s = (a_s^1, \dots, a_s^T)$ with $a_s^t \in \{0, 1\}$ is introduced to govern availability of battery charging and discharging under price-based control and the following ϕ_s domains obtain:

$$\phi_s^t \in [a_s^t \underline{\phi}_s, a_s^t \overline{\phi}_s], \text{ where } a_s^t = \begin{cases} 1 & \text{if } p^t < \underline{p} \text{ or } p^t > \overline{p}, \\ 0 & \text{otherwise.} \end{cases} \tag{5.5}$$

Maximum discharging and charging power are denoted by $\underline{\phi}_s$, respectively $\overline{\phi}_s$. The thresholds $\underline{p}$ for charging and $\overline{p}$ for discharging can be adapted to control battery activity in order to improve power system efficiency. To determine reasonable threshold levels some basic statistical information of the electricity prices (e.g., distributional properties) is required. For the ease of exposition, population-wide price thresholds specified as quantiles of the simulation period's price distributions are assumed.

For charging amounts (ϕ_v) of an EV $v \in \mathcal{V}$ the following optimization problem is obtained:

$$\min_{\phi} \sum_{t=1}^{T} p_t \cdot \phi_v^t \tag{5.6}$$

$$\psi_v^t \overline{b}_v = \psi_v^{t-1} \overline{b}_v + \phi_v^t - \gamma_v^t, \tag{3.18 revisited}$$

$$\psi_v^0 = \psi_v^T, \tag{3.19 revisited}$$

where the former constraint ensures continuity of the battery level (ψ_v). The latter requires equal levels for initial (σ_v^0) and terminal (σ_v^T) battery levels to avoid complete discharging at the end of the optimization horizon. Charging capacity ϕ_v for EVs is limited in the interval $[0, \overline{\phi}_v]$.

5.2.2 Solution Procedure

Under indirect load control retail electricity rates are assumed to reflect the generation of RES and low retail prices correspond with high availability of renewable output. The rates are updated weekly and published in advance. This leads to a two step simulation approach for decentralized load control (open-loop) where first, retail electricity rates are calculated and transmitted to the residential devices which individually optimize their operation schedule. Then, the power system model is executed using the device schedule and the RES generation as input data to determine the conventional generation (CG) dispatch serving the residual load not covered by renewable generation. Figure 5.2 shows the simulation flow for decentral decision-making via indirect load control. To integrate uncertainty in renewable energy sources retail electricity rates can be built on a forecast of renewable generation. Closed-loop control requires an additional feedback loop for adapting the electricity rates after the scheduling decision of a device.

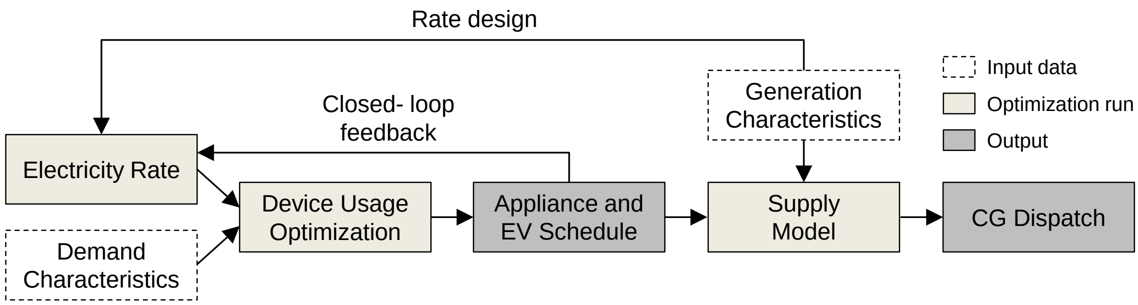


Figure 5.2: Overview of simulation flow for indirect load control

5.2.3 Performance

To determine cost minimal operation times, the device implementations of the direct load control model can easily be adapted. Optimization horizon, population size and the set of flexible appliances remain the main influence factors for runtime. Table 5.1 shows the effect of these three parameters and includes a comparison of average simulation runtimes between centralized and decentralized load control. EV and battery shares are constant for all populations and runtime estimations presented in the figure are based on five replications of the simulation.

Average runtimes for centralized and decentralized control are very similar for small population sizes. For larger populations the increasing computational complexity of centralized regimes becomes obvious. Decentralized control largely improves runtime for weekly optimization beyond a population size of 1,000 households and for daily optimization beyond 10,000 households. For the full set of flexible devices centralized control for 10,000 households over one week is computationally intractable. However, under decentralized control a load schedule for this setting can be calculated in about 600 seconds. Further, decentralized control allows to create operation schedules for large populations with 100,000 households but a small set of flexible appliances, e.g., storage space and water heaters in a fraction of the time as compared to centralized control.

Table 5.1: Average simulation runtimes for various calibrations of centralized and decentralized control

		Optimization horizon			
		Day		Week	
Pop. size	Flexible Appliances	Centralized Average runtime [s]	Decentralized	Centralized Average runtime [s]	Decentralized
10	Full set	0.5	0.2	1.2	1.1
100	Full set	0.7	1.2	11.0	6.7
1,000	Full set	10.8	13.0	341.5	65.1
10,000	Full set	344.2	103.8	Out of memory	615.7
100,000	Stor. heater	85.0	0.5	716.0	4.0

5.3 Model Setup

The indirect load control model is a possible instance to realize a decentralized control regime. After the introduction of a formal description, in this section two model setups are specified to evaluate price-based coordination mechanisms. These setups serve to explore rate design options for indirect load control aiming to reduce load synchronization and improve efficiency in a power system with a high share of renewable generation.

Despite the performance drawback of centralized control for large scale application, it can establish an optimal benchmark for alternative coordination mechanisms (Ramchurn et al., 2011; van den Briel et al., 2013). In order to facilitate benchmarking of decentralized control mechanisms, runtimes of the direct load control model limit population sizes. The simulation horizon covers 12 week discretized on 15-minute intervals. To focus on coordination mechanisms, it is instrumental to reduce complexity of the model and apply a simple evaluation scenario with a single flexible load type. Therefore, electric vehicle charging is a prime candidate which often serves as a representation for flexible loads (Blumsack and Fernandez, 2012; Andersen et al., 2009). EVs are ideal for DR as they are large and flexible loads. Thus, for analyzing basic rates and design elements a simplified model representing a residential area with 900 static residential households each equipped with an EV is assumed (simple scenario). In this system flexible EV charging accounts for 35 % of total electricity consumption. Further, a supply portfolio with wind as sole renewable source is deployed. As the EV model is built on real driving profiles, stochastic influence on the demand side is ruled out. For deterministic EV charging evaluations are based on a single simulation run.

After establishing an understanding of price-based load coordination using the simplified model, group pricing is evaluated in a more comprehensive scenario to derive insights for a greater number of real-world power systems. Therefore, the base scenario defined in the previous chapter is applied using the demand model with the full set of flexible devices and a mixed generation portfolio. As a reminder, in the base scenario a population of 1,000 households with 16 % EV and 2.5 % stationary battery penetration is simulated. Flexible loads comprise household appliances including washing machine, dishwasher, dryer, refrigerator, freezer, and storage water and space heater but also the emerging technologies electric vehicles and stationary batteries. On the supply side an equally weighted mix of PV and wind is assumed for the generation portfolio. The full specification of the base scenario is given in Table B.1.

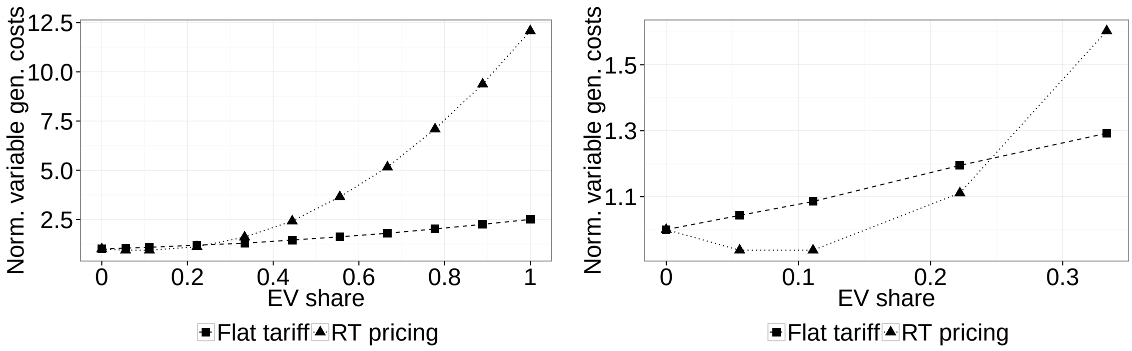
5.4 Price-based Control of Residential Load

While price-based incentive schemes seem to be a straight-forward form for decentral coordination in smart grids, their applicability for automated DR has been seen more critical as they may induce new load peaks due to herding effects. Initially, these results are revisited by analyzing system efficiency under posted pricing schemes. Therefore, the simple scenario is utilized and vehicle charging serves as representation of flexible loads. This approach serves to assess system costs under posted pricing schemes for different shares of flexible demand in the system. Then, standard rate designs (real-time, time-of-use and high-low pricing) are applied to reproduce the well-known herding effects and to identify key factors causing load synchronization.

5.4.1 System Costs for Different Flexible Demand Shares

Load synchronization or herding appears as a large number of devices operate at the same time. Thus, one driver for the extent of load synchronization is the number of flexible units in a system. For this analysis flexible loads are instantiated with EVs. Further, two different charging strategies for the EVs are used. Under a flat electricity tariff EVs perform AFAP charging. Smart charging facilitates a cost minimal charging program using RT pricing as incentive. This RT tariff directly reflects the difference between current renewable generation and base load that is $p \sim G^t_{RES} - L^t_B$. In Figure 5.3 variable generation costs for different EV penetration levels under the two charging strategies are shown. The scenario without EVs in the system serves as a reference where generation costs are normalized to.

In line with the results of Sioshansi (2012) it can be be observed that for low penetration of flexible load posted real-time prices decrease variable generation costs. The decreasing variable generation costs show that real-time prices properly signal the marginal cost of electricity generation. Yet, with EV penetration level slightly above 20 % real-time pricing increases costs as compared to a flat tariff. If a fairly low number of flexible units reacts to the same incentive, load synchronization starts to degrade system efficiency and thus increase variable generation costs. At a penetration of 100 % EV charging doubles variable generation costs under a flat tariff. Under RT pricing generation costs increase by more than 12 times.



(a) Broad range of flexible load shares (b) Detailed view for low flexible load shares

Figure 5.3: Variable generation costs for different shares of flexible loads

5.4.2 Load Patterns Under Basic Rate Structures

In a power system with a large share of flexible loads, herding might threaten system efficiency. In the following, the well-known load synchronization under basic electricity rates is reproduced to identify key factors causing herding and thus providing a starting point for desynchronization approaches. Therefore, an EV penetration of 100 % is assumed resulting in a large share of flexible loads in the system and thus stressing load synchronization under the basic rates. For each pricing scheme, the aggregate EV charging load, the net renewable generation and the cumulative conventional generation employed for one example week are shown. The numerical results are obtained using the scenario described in Section 5.3.[3]

Flat Electricity Tariff

The left panel of Figure 5.4 depicts the aggregate charging loads of a fleet of EVs under a flat tariff, i.e., following the AFAP charging strategy. Under this strategy EVs charge whenever possible with the maximum charging amount available. Thus, AFAP charging only depends on the availability and technical specification of the charging infrastructure and on the driving behavior including (i.e., trip timing and distances). It can be observed, that charging loads are evenly distributed and spikes can largely be avoided. Under a flat tariff there is no incentive to shift EV charging

[3]The analyses presented subsequently contain parts of our working paper Flath and Gottwalt (2014).

activity. Hence, charging often takes place in times with no or very limited renewable generation available. Consequently, in many situations conventional generation is needed while in others available renewable generation remains unused.

Real-Time Pricing

Under RT pricing, the retail price reflects the delta between renewable generation and base load ($p \sim G^t_{RES} - L^t_B$). This rate structure is illustrated in the upper right panel of Figure 5.4 for one example week. If EV owners base their charging decision on this ex-ante specified tariff, a high concentration of EV loads can be observed (see lower part of Figure 5.4). Such herding effects are in line with results from prior research on the effects of price-based coordination in retail electricity markets. At the same time, concentrated EV charging—in this example scenario—greatly exceeds available renewable generation and requires a large amount of conventional generation. It is evident from the figures, that over-coordination occurs because of the presence of distinct time slots with minimal costs to which the flexible loads will respond in a common manner.

Time-of-Use Pricing

Time-of-use (TOU) electricity tariffs can mitigate the load spikes observed under RT pricing as they constrain the rate structure to a limited number of intervals with the same price level (rate zone) and this way remove individual low prices. Previous contributions identify load peaks also for price-based load control with TOU prices (e.g., Ramchurn et al., 2011). TOU tariffs are created such that the price levels and length of the rate zones minimize the deviation from the RT price presented before. To this end, a rate design model based on mixed-integer optimization (Flath, 2013a) is applied and the total number of rate zones is fixed at fourteen (approximately two rate zones per day). The resulting TOU tariff is depicted in the upper left part of Figure 5.5. TOU rates indeed reduce the over-coordination phenomenon compared to RT pricing regimes. The lower part of the figure shows that EV charging load is more distributed and maximum load levels are reduced. However, still distinct new load peaks can clearly be identified at the end or beginning of intervals with low prices.

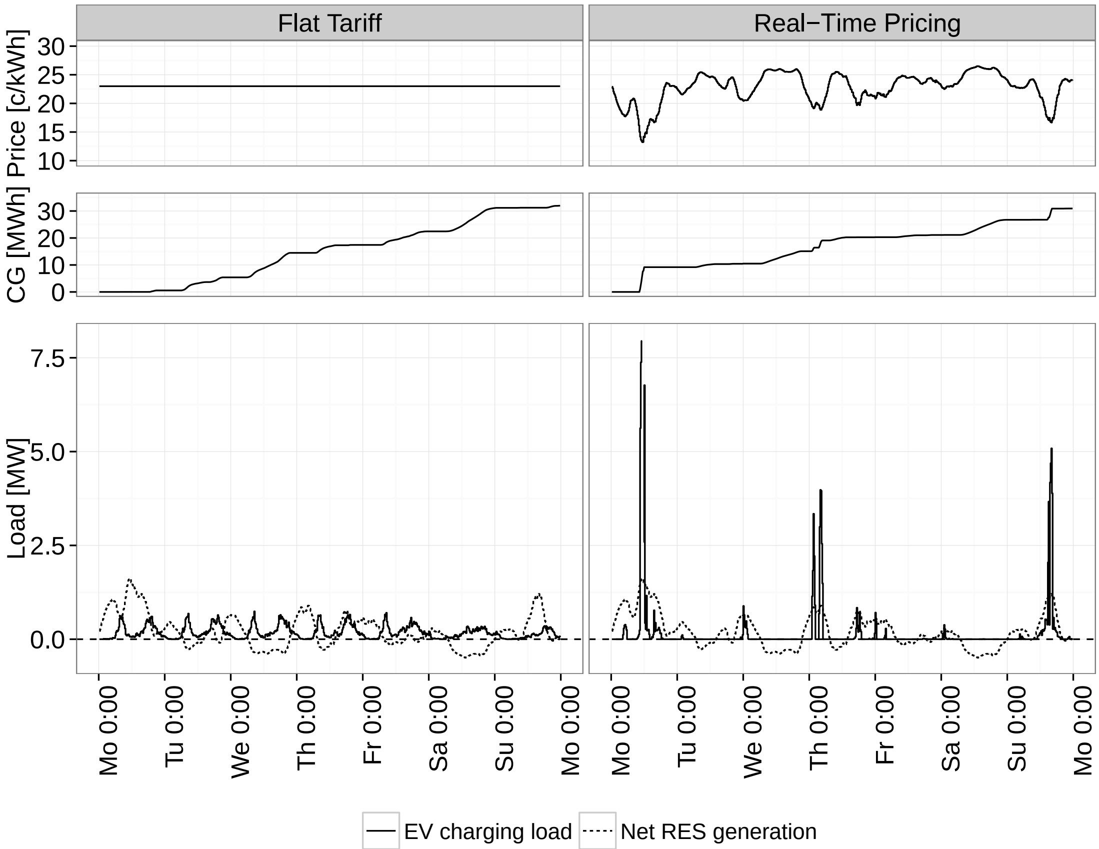


Figure 5.4: Rate structure, cumulative conventional generation (CG) and EV charging load for a flat tariff and real-time pricing

One reason for the load clustering at the boundaries of the lowest price intervals is due to the optimization's tie-breaking procedure between intervals with identical prices. Furthermore, under TOU rates EV charging exceeds available renewable generation and conventional generation requirements remain at a high level.

The results from TOU pricing indicate that less pronounced minimum price levels do indeed reduce load peaks. The TOU tariff can be further simplified by limiting it to only two price levels. For this tariff a low price is assumed when available wind generation is above a threshold level and a high price in all other times. The resulting high-low price for the example week is depicted in the upper right part of Figure 5.5. The lower part of the right panel in the Figure shows the charging load for EVs under such a tariff. Under High-Low Pricing (HL) vehicle charging is more distributed and peaks are reduced compared to the TOU tariff. Smaller peaks remain at the boundaries of the low price intervals.

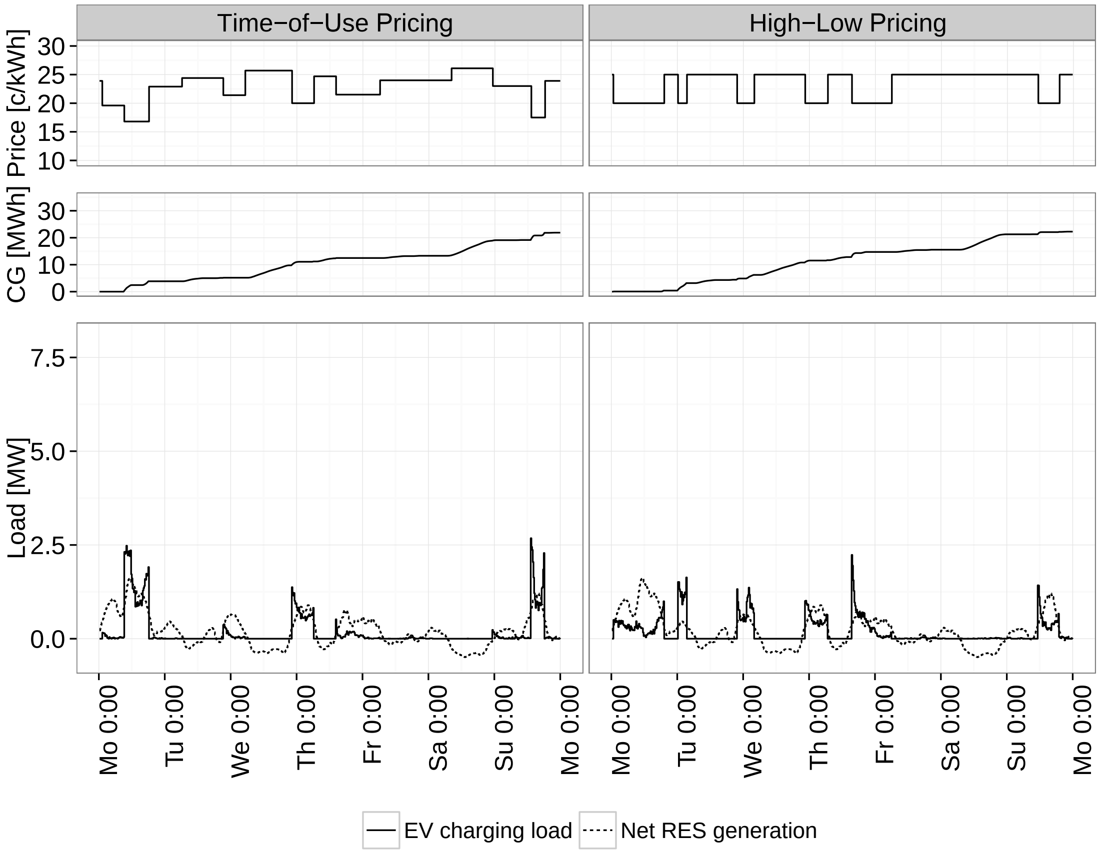


Figure 5.5: Rate structure, cumulative conventional generation (CG) and EV charging load for time-of-use and high-low pricing

5.5 Load Desynchronization

With a fairly low number of flexible units, basic rate structures can cause peak loads and renewable generation often remains unused. A load aggregator coordinating flexible residential demand using one of these rates cannot expect to reduce variable generation costs. This section develops additional design elements (power surcharges, randomized group rates) to reduce load synchronization. Exemplary figures illustrate rate structures and charging loads and guide the discussion of desynchronization approaches.

In addition, the rate modifications should allow to exploit available renewable generation under exogenously specified retail electricity rates and thus enable a more efficient price-based control of flexible residential load. To this end, a more extensive simulation of different coordination approaches is provided and load distribution and variable generation costs are reported for a 12 week simulation period. Finally, the load desynchronization approaches are investigated in more detail to provide design guidelines for implementation.

5.5.1 Different Approaches

Under TOU and HL rates load is clustered at the borders of low price intervals. To avoid this clustering a power-based surcharge on top of the basic electricity rates is introduced. Another reason for over-coordination is the common manner in which all EVs respond to the same tariff. Thus, individualization of electricity rates is proposed and charging behavior under group rates is evaluated. Further, a benchmark case of adaptive closed-loop pricing is also considered for comparison.[4]

Power-based Surcharge

A key reason for load clustering is the bang-bang structure of charging decisions (i.e., charge at full power or do not charge) under energy-only pricing for individual vehicles. If several EVs charge at full speed at the same time load synchronization occurs. To obtain intermediate charging levels and to incentivize a more spread-out charging behavior, a (very small) power-based price surcharge ψ_p can be introduced. In this thesis a quadratic formulation of the objective function for individual EV charging optimization is applied:

$$\min_{\phi_v} \sum_{t=1}^{T} p^t \phi_v^t + \psi_p (\phi_v^t)^2 \tag{5.7}$$

Combined with RT pricing, very small charging power costs can not change the ranking of the prices as the absolute distances in electricity prices dominate the

[4] This section is an adapted version of our working paper Flath and Gottwalt (2014).

cost term. A higher surcharge value spreads out charging behavior but dilutes the incentives of RT pricing. Hence, a power-based surcharge is applied for TOU and HL pricing only.

The left panel of Figure 5.6 depicts the EV charging load under TOU pricing with a power-based surcharge (TOU-P). For this analysis, the surcharge takes the value $\psi_p = 1.0$. Higher charging power levels are now costly. Consequently, customers still aim to charge in low cost TOU zones but distribute their charging demand more evenly. This way, load spikes can largely be reduced compared to standard TOU pricing. The power-based surcharge improves the coverage of load by available renewable generation since load spikes and excess charging in hours with high generation from renewable sources are reduced. A power-based surcharge leads to more evenly distributed load. However, load is still mainly concentrated in the three minimum price intervals. The absolute distance of the price levels impedes shifting into other potentially desirable times for EV charging.

For high-low pricing with a power surcharge (HL-P), a more spread-out charging behavior can be observed as well (see right panel of Figure 5.6). The power-surcharge mitigates peaks at the boundaries of the low price intervals. Due to the fact that only two price levels exist, many hours have the same low price level and EV charging is more evenly distributed. Peaks are largely reduced as compared to RT and TOU pricing and approach the levels of flat pricing. Furthermore, the need for conventional generation decreases as well.

Randomized Group Pricing

The results from power-based surcharges show that modifications of the basic rate can greatly decrease peak load. Individualization of retail rates is another possibility to reduce load synchronization. To this end, Muratori (2014) proposes the idea of “Multi-TOU" where distinct tariff signals are distributed to a limited number of consumer pools. In the work at hand this approach is generalized in the form of Group Pricing (GR) which allows greater differentiation up to personal pricing. Under this price regime customers are assigned to groups and all members of one group receive the same electricity rate. The idea of group pricing extends today’s control

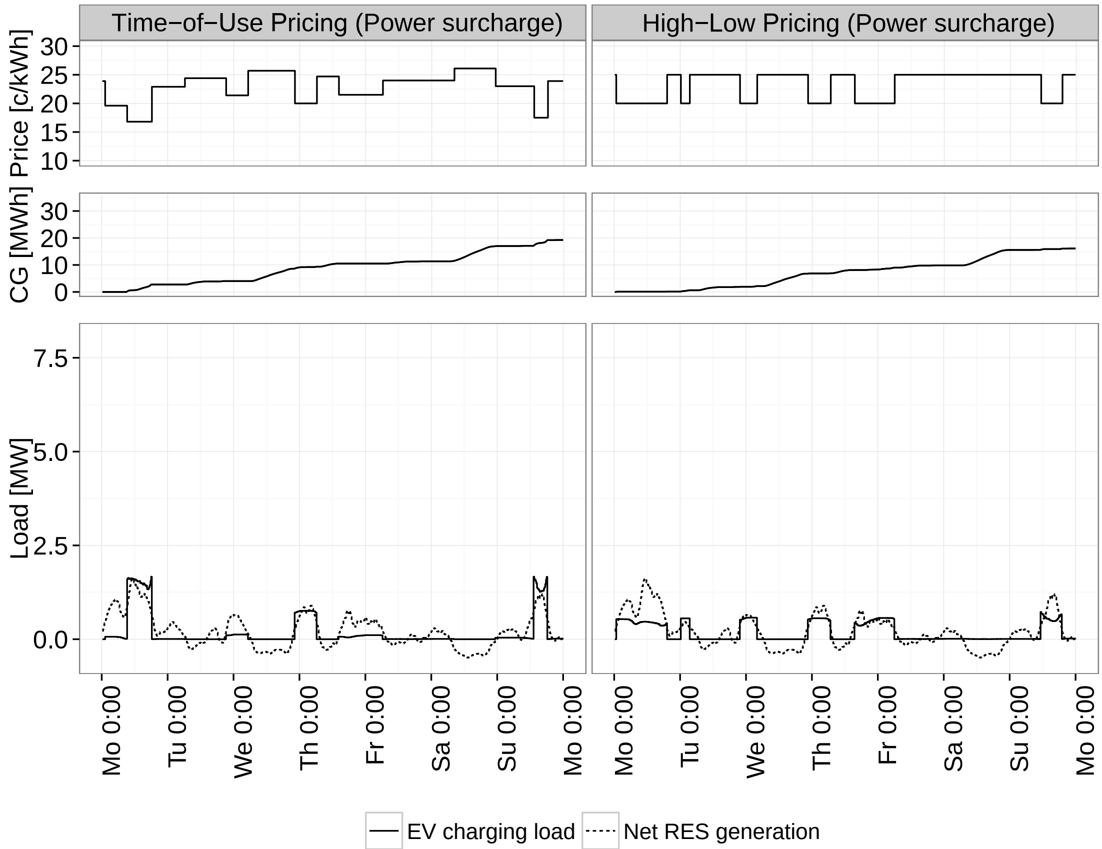


Figure 5.6: Rate structure, cumulative conventional generation (CG) and EV charging load for time-of-use and high-low pricing with power surcharge

of storage heaters in residential households.[5] For an electric utility the application of group pricing requires three basic decisions: (i) determine the number of different groups, (ii) assign customers to groups and (iii) specify a rate for each group.

In the following, various group sizes (i) are investigated. In the limit a group consists of a single customer which corresponds to fully individualized electricity rates. With respect to (ii), groups of equal size are applied and EVs are randomly allocated to the groups.[6]

[5] Grid operators determine groups of storage appliances and transmit via ripple control operation intervals on group level to desynchronize these large loads Hastings (1980).

[6] Alternative group formation methods (e.g., best fit on total load) did not lead to substantially different results.

Recent research contributions have put forward the application of randomization to mitigate over-coordination problems in decentralized power system. For example, Shinwari et al. (2012) assign operation probabilities for shiftable loads to local control agents. Probabilities for starting shiftable loads are high in hours with low non-shiftable load in the system. Van den Briel et al. (2013) extend this approach by determining operation probabilities based on the non-shiftable loads. They present three options to calculate these adapted operation probabilities. Kishore and Snyder (2010) apply a stochastic admission control scheme from the telecommunications sector to avoid simultaneous load occurrences. In a similar fashion, Gong et al. (2012) demonstrate that randomized charging for electric vehicles can reduce transformer wear. While these approaches illustrate the *power of randomness* to break the problem of price-induced over-coordination of loads, they do not characterize appropriate incentive structures that induce truthful behavior of system participants. Following this line of thought randomization is applied to create group-specific rates (iii): Random group prices (r^t) are determined by adding noise (ϵ^t) to an underlying RT rate,

$$r^t = p^t + \epsilon^t. \tag{5.8}$$

A truncated normal distribution is applied for the noise with $\epsilon^t \sim \mathcal{N}^T(0, \sigma, -p^t, \infty; x)$. The standard deviation σ reflects how different the group-specific price vectors should be. The truncation on the support $[-p_t, \infty[$ avoids negative retail electricity prices. The density function of the truncated normal distribution with support $[-p^t, \infty[$ is given by:

$$\phi\left(0, \sigma, -p^t, \infty; x\right) = \begin{cases} 0 & \text{if } x \leq -p^t \\ \frac{\phi\left(0,\sigma^2;x\right)}{\Phi(0,\sigma^2;\infty)-\Phi(0,\sigma^2;-p^t)} & \text{if } x > -p^t. \end{cases} \tag{5.9}$$

Figure 5.7 depicts the aggregate EV load for 20 groups and two different standard deviation levels for tariff randomization, $\sigma \in \{1, 4\}$. Remember that the EV fleet consists of 900 vehicles, which corresponds to 45 vehicles per group. Looking at aggregate EV charging load, it can be seen that for a randomization level of $\sigma = 1$ charging takes place mainly in three intervals during the week. Hence, EV charging load achieves similar synchronization as compared to RT pricing and greatly exceeds available renewable generation. Consequently, conventional generation requirements remain at a high level only slightly below RT pricing. More promising results can be achieved with a randomization level of $\sigma = 4$. Here, total load is more distributed and renewable generation can be exploited. Thus, coordination with respect to both goals (peak load reduction and load coverage) is improved. A low standard deviation for generation of group prices is not able to adequately change the ranking of prices and prevent over-coordination.

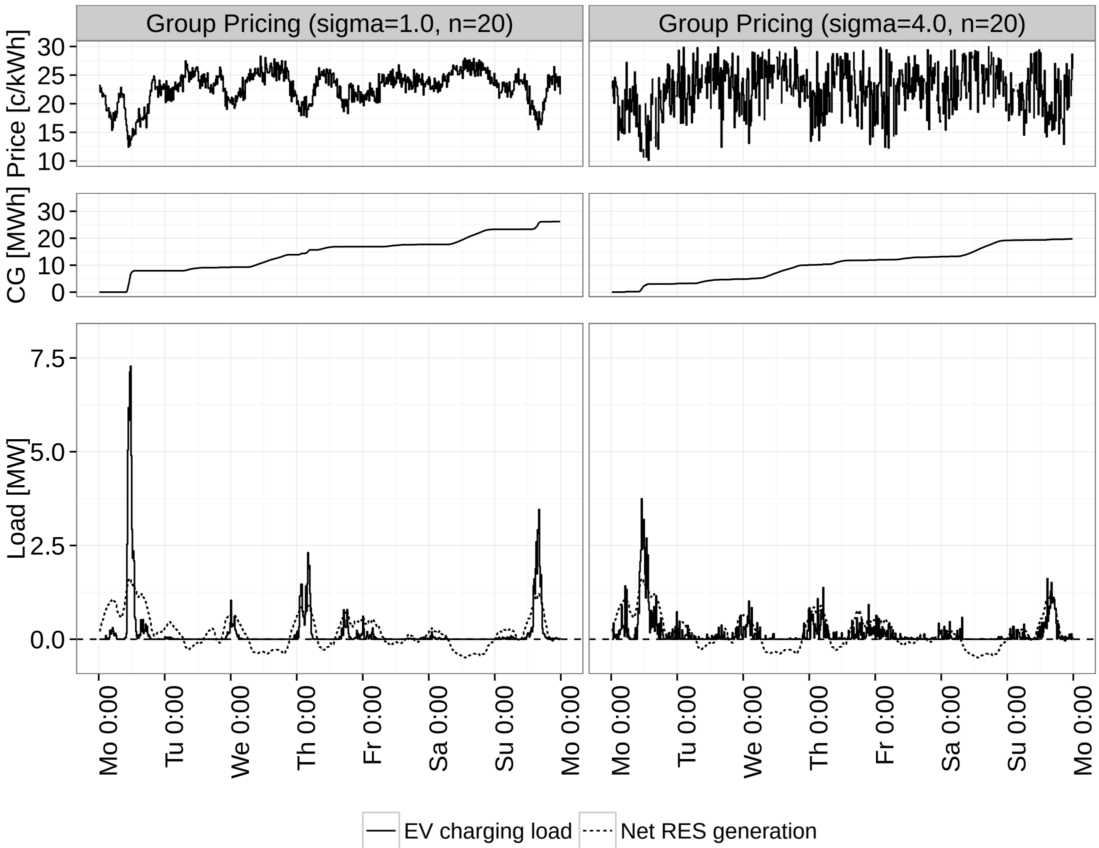


Figure 5.7: Rate structure, cumulative conventional generation (CG) and EV charging load for 20 groups with two randomization levels

Group pricing reduces over-coordination and at the same time induces load-shifting to hours with net availability of renewable generation. More groups, i.e., fewer EVs per group, may also reduce system peaks. In Section 5.5.5 the effects of randomization and group size on load synchronization and load covered through electricity from renewable sources is discussed in more detail.

Closed-loop Adaptive Prices

In contrast to the above described pre-specified price regimes, closed-loop price signals are adapted in response to customer actions (Mohsenian-Rad et al., 2010). This facilitates more efficient load coordination yet burdens customers with unreliable price signals and introduces complexity into market communication for billing and transaction verification. Therefore, closed-loop adaptive pricing (Adapt) is considered only as a theoretic benchmark to compare novel open-loop control schemes against. It is assumed that EVs sequentially make their charging decisions for one week. The net renewable generation is the base for determining a customer's rate offering and is adapted after each charging decision. Thus, each EV receives a unique tariff determined by the net RES generation and the charging decisions of previous vehicles. The upper part of Figure 5.8 depicts prices faced by different customers. The first EV receives the basic RT price. Due to lower net generation availability, prices for subsequent customers increase during the times where charging already has been scheduled. Consequently, customers acting later will face rate structures where the price valleys have been filled.

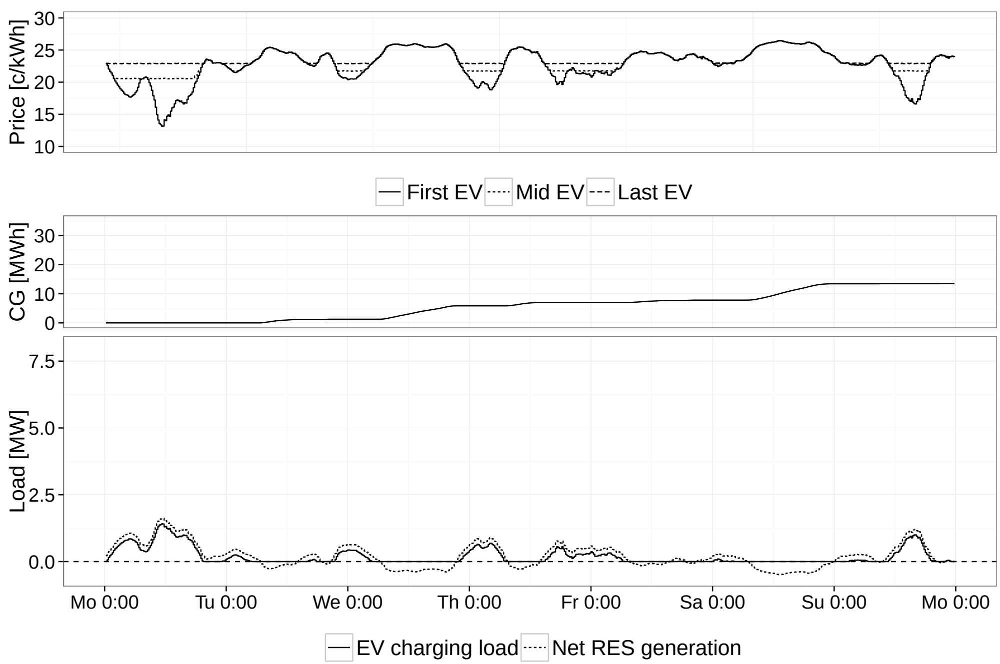


Figure 5.8: Example rates, cumulative conventional generation (CG) and EV charging load for closed-loop control

Frequent tariff actualization signals RES availability to the vehicles such that under adaptive prices aggregate charging load perfectly follows the shape of the net wind generation (lower panel of Figure 5.8) and undesired load concentrations are completely ruled out. Conventional generation is only required when it is absolutely necessary, e.g., if inflexible base load exceeds available renewable generation.

5.5.2 Generator Capacity and Output

So far an example driven-style for the discussion of various price-based control mechanisms has been employed. For a more extensive analysis and to facilitate comparison of different coordination mechanisms total conventional generation, capacity requirements for conventional generation, and the maximum EV charging load are analyzed (see Table 5.2).[7] Numbers in the table origin from a 12 week simulation of the simple scenario with flexible EV charging and wind as volatile renewable source. Naïve charging (Flat) serves as a basis and the values in the table are normalized accordingly. In addition to the rates presented, a direct control scenario is evaluated where charging is scheduled centrally as an optimal benchmark (OPT).

The closed-loop control scheme with an adaptive tariff (Adapt) avoids load synchronization and requires the same conventional generation capacity as the benchmark scenario (OPT). Results for maximum EV charging in Table 5.2 are in line with the observations described before. RT and TOU tariffs lead to over-coordination for flexible EV charging load which can almost entirely be avoided by applying the modifications of the basic rates. In the table EV charging peaks depict the load synchronization under different coordination mechanisms.

In terms of the power system, concentration of EV charging requires high and costly electricity generation capacity. Under power surcharges for high-low (HL-P) and time-of-use (TOU-P) rates lower conventional generation capacities are required. The performance of group pricing largely depends on the number of groups and the standard deviation values. The scenario with 100 groups and a noise level of $\sigma = 3$ (GR 100-SD3) reduces the required conventional generation capacity to a great extent as compared to the basic rates. Interestingly, while uncoordinated

[7]This section is an amended version of our working paper Flath and Gottwalt (2014).

charging (Flat) shows the lowest synchronization level it does not show the lowest capacity for conventional generation as charging will sometimes occur in the absence of renewable generation.

Table 5.2: Normalized values for maximum EV charging, capacity requirements for conventional generation (CG) and total conventional generation amount

Scenario	Max. EV charging	CG capacity	Total CG usage
Benchmark			
OPT	1.49	0.489	0.602
Adapt	1.9	0.489	0.603
Group Pricing			
GR900-SD5	3.86	0.978	0.666
GR100-SD4	5.46	1.76	0.679
GR100-SD3	6.44	2.45	0.697
GR20-SD3	7.57	3.42	0.748
Power Surcharge			
TOU-P	4.77	2.33	0.737
HL-P	6.02	3.75	0.69
Basic Rates			
Flat	1	1	1
TOU	9	4.65	0.834
HL	9.64	6.22	0.822
RT	13.1	8.39	1.02

The total amount of conventional generation indicates the overall usage of available renewable generation. Under a flat tariff (AFAP charging) load is distributed. Yet, the total amount of conventional generation is almost doubled as compared to the optimal scheduling and second highest across all scenarios. EVs cannot exploit high generation and charging frequently requires additional conventional generation in times with low renewable generation availability. Thus, a large value for total conventional generation indicates a low overall coverage of load through electricity available from renewable sources. Low cost renewable generation is not exploited and costly conventional generation is required to supply charging requirements at other times. Naïve or simple charging avoids load synchronization, though unused flexibility potentials decrease system efficiency.

Table 5.2 also depicts that over-coordination not only leads to system peaks but also deteriorates load coverage as RT pricing requires even higher conventional generation amounts than naïve charging. Due to the concentration of EV loads to few times, charging largely exceeds renewable generation. Simultaneously, other hours with slightly less renewable generation are completely neglected under RT pricing. Power-based surcharges and randomized group pricing reduce the conventional generation amount to two thirds of naïve charging. The results in the table show that the modifications in retail electricity rates not only decrease EV charging peaks and the required power generation capacity, but at the same time decrease the total output of conventional generation.

5.5.3 Aggregate System Costs

For a comprehensive assessment of the retail electricity rates and their modifications the analysis is extended beyond conventional generation usage and load synchronization and the effects on the overall power system are evaluated.[8] The model of the stylized power system penalizes both total amount *and* high concentrations of conventional generation. Figure 5.9 shows mean values and standard errors for the weekly variable generation costs. Costs are again normalized to uncoordinated charging (Flat). In the left panel all scenarios are depicted. For RT, TOU and HL pricing weekly costs are mostly higher than AFAP charging under a flat tariff.

As described before, the charging activity in the scenarios RT and TOU is concentrated in only a few hours during the week and hence induces new load peaks and increases variable generation costs. Note that under TOU pricing less total conventional generation than under a flat tariff is required (see Table 5.2). Yet, a TOU rate results in higher overall variable system costs due to increased costs in peak hours. These results confirm Sioshansi's findings (Sioshansi, 2012). The HL rate is characterized by a high number of hours with the same, low price. Hence, EV charging load is more evenly distributed. Still, all vehicles receive the same tariff and load concentrations at the boundaries of low price intervals increase variable

[8] A slightly adapted version of this chapter is also part of our working paper Flath and Gottwalt (2014).

generation costs. At the same time the HL rate only has low prices in hours of above threshold renewable generation availability, leaving low generation hours unused.

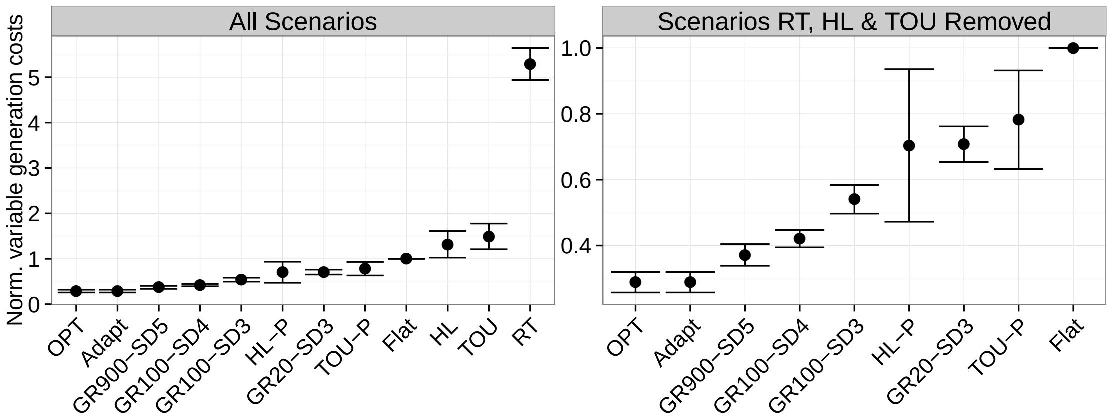


Figure 5.9: Normalized variable generation costs for different coordination mechanisms

To increase system efficiency, a meaningful coordination approach must at least outperform uncontrolled charging. Figure 5.9 shows that all suggested modifications for retail electricity rates reduce variable system costs below the costs of AFAP charging (Flat). The application of the two rates with a power-based surcharge (see TOU-P and HL-P), decreases variable generation costs by about 50 % compared to the respective basic rate. For the TOU-P rate the smaller number of low price hours and the gap between price levels impede EV charging to be more distributed. Thus, load from EV charging can be flattened via power surcharges, but still remains fairly concentrated in a limited number of hours resulting in costly conventional generation requirements. Therefore, the TOU-P rate encounters higher variable generation costs as the HL-P regime. Also surcharge-based coordination exhibits large fluctuations as signified by the large error bars. Group pricing further decreases variable generation costs as it reduces load peaks while retaining the ability to use available renewable generation. The performance of group pricing largely depends on the number of groups and the randomization level of the tariff. While a simple group pricing scheme (GR20-SD3) performs only slightly better than uncontrolled charging, individual pricing (GR900-SD5) can almost achieve the optimal benchmark level. Hence, confirming on system level the potentials an individualization of electricity rates via randomized group pricing might provide.

5.5.4 Mechanics of Coordination Approaches

Given the large differences in variable generation costs, an insight in the inner workings of the different coordination approaches is provided. To this end, variable generation costs and charging shares are mapped to the distribution of wind output. By showing the emergent behavior under different retail rates and the optimal benchmark of central control, typical coordination failures can be identified. Figure 5.10 provides these shares for the known scenarios. The y-axis shows classes for the renewable generation output levels.

For the integrated scheduling and dispatch scenario (OPT), it can be observed that about 20 % of total EV charging takes place in the 12.5 % slots (in the figure class 87.5 % to 100 %) with the highest wind generation. Overall a large share of total charging takes place in hours with high renewable generation, meanwhile, only minor variable costs accumulate here. EV charging activity in low generation hours is due to missing flexibility. The high variable cost share in the 25 % quantile of renewable generation output is due to conventional generation dispatch for supplying base load. For the uncontrolled scenario (Flat) charging shares are almost evenly distributed among the renewable generation quantiles. Variable costs for uncontrolled charging are similarly distributed as for the optimal benchmark. The higher total generation costs can be explained by the distribution of charging load: for flat pricing only a small share of charging takes place in the high generation quantiles leaving the free of charge available renewable generation unused.

It can easily be seen that RT and TOU pricing tend to over-coordination as they accumulate a large share of EV charging in high generation hours. According to the charging distribution for the optimal benchmark a considerable amount of charging activity can take place in times with medium renewable generation output (see classes 37.5 % to 75 % in the figure) with a minor increase in variable costs. RT and TOU schemes mostly omit charging in these times. Hence, the load concentrations for RT and TOU pricing are costly due to the unused renewable generation and due to the increasing variable costs in hours with load synchronization.

The simplest basic rate with only two price levels (HL) is able to reduce load concentration in the times with highest renewable generation (class 87.5 % to 100 %)

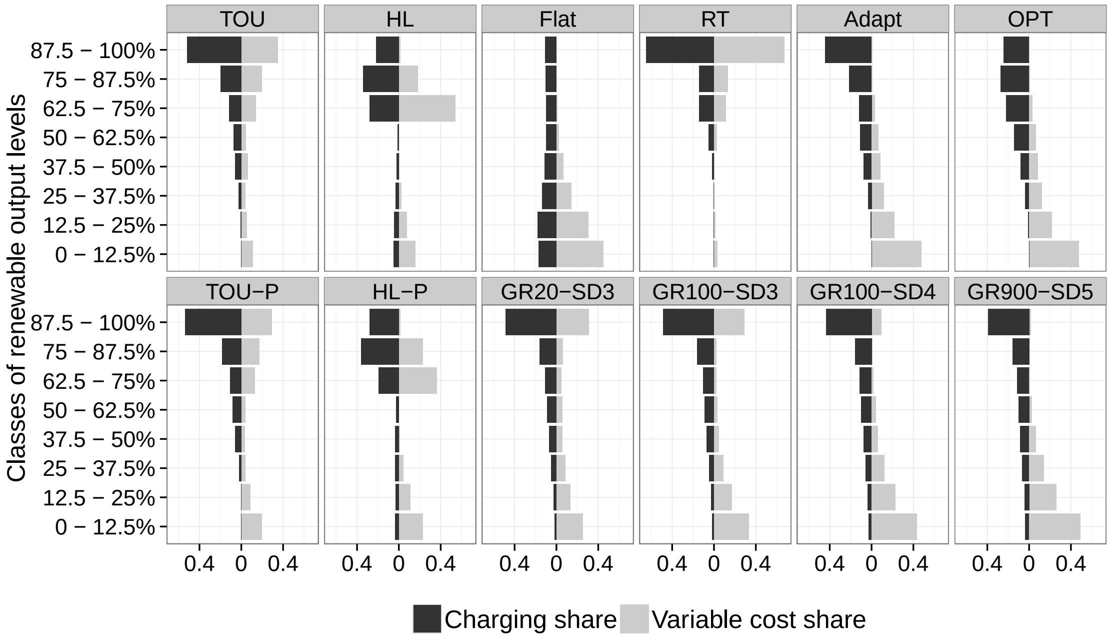


Figure 5.10: Charging shares and variable cost shares for different classes of renewable generation output levels

and spreads charging load more evenly. Under a power-based surcharge (HL-P) hardly any changes in charging shares compared to a sole HL scheme can be seen. Yet, the share of variable costs in the classes 65.5 % to 87.5 % is greatly reduced. The observation that the power-surcharge mitigates load peaks at the boundaries of low price intervals explain this cost reduction (see Figure 5.6).

Interestingly, for all depicted randomized group pricing regimes a very similar distribution of charging loads can be observed. The only visible change is a slight decrease of charging load in the highest quantile. At the same time, variable cost shares in high generation hours largely decrease with more groups and higher standard deviation values. Comparing the costs in the class with the highest renewable generation output for the four group pricing scenarios reveals this observation. It can be concluded that group pricing achieves variable generation cost reduction by load desynchronization in the highest renewable generation hours.

Overall, modified open-loop coordination via group pricing and power-based surcharges can reduce variable generation costs in two directions. Firstly, modified rates reduce load synchronization and thus costly peaks of conventional generation. Secondly, they increase overall load coverage with RES by reducing the extreme reliance on times of high renewable generation.

5.5.5 Design Guidelines

Power-based surcharges and group pricing achieve promising results with respect to over-coordination, load coverage and variable generation costs. To better understand their application in practice, they are investigated in more detail to provide design guidelines for implementation. Hence, for electricity rates with power-based charges the effects of different surcharge values and for randomized group pricing noise levels and the number of groups are analyzed.

Power-based Surcharge

Clearly, the choice of ψ_p is central for the effectiveness of power-based surcharges. Figure 5.11 illustrates aggregate charging loads for three different surcharge values, $\psi_p \in \{0.1, 1, 10\}$. Reducing the surcharge value to $\psi_p = 0.1$ does not affect distribution of charging. This can be observed in the left and mid panel of the figure which depict similar charging loads. Both surcharge values distribute load in the same TOU steps and are too small to incentivize charging in hours with higher retail prices.

This can be achieved by a higher surcharge level which shifts the aggregate charging load to other TOU price intervals and reduces load concentration. The right panel of the figure shows the aggregate charging load for $\psi_p = 10$. However, the high surcharge dilutes the TOU incentives indicating renewable generation availability. In the example week, this results in EV charging activity even at times with negative net renewable generation (Tuesday and Friday before noon).

While in principle an effective means for load desynchronization, a power-based surcharge entails some limitations for real-world application. Many electric appliances must run in one continuous stretch and cannot adapt their power consumption as they have a fixed load profile. Yet, they still exhibit large temporal flexibility

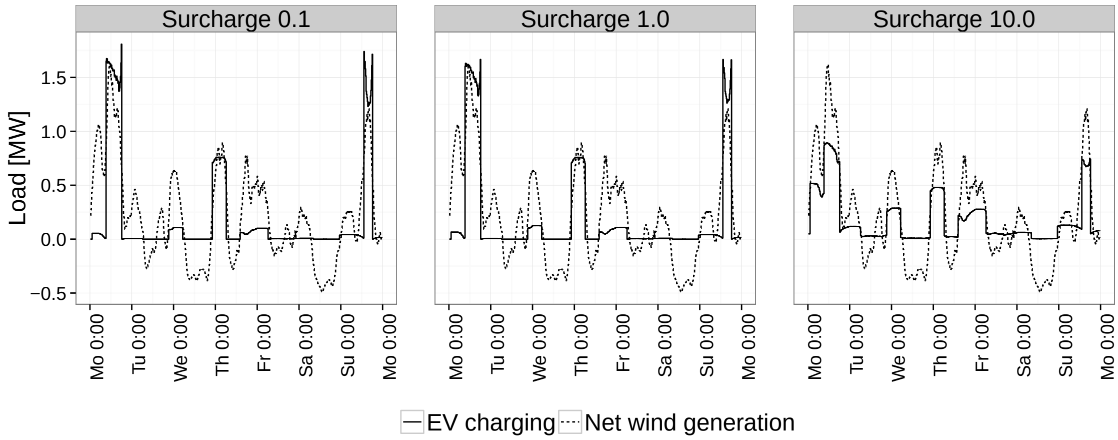


Figure 5.11: EV charging load under a TOU regime for three surcharge values

with respect to start time selection. For these loads, the introduction of power-based surcharges cannot mitigate load clustering. Alternatively, rational customers with various appliances would schedule the complete load in their portfolio avoiding the simultaneous operation of appliances. Furthermore, load-based surcharges can induce inefficiencies as they penalize individual consumption in uncongested situations (Bohn, 1982).

Randomized Group Pricing

For the efficacy of group pricing the randomization level and the number of groups are the key parameters.[9] Figure 5.12 depicts the 97.5 % load quantiles over a 12 week simulation period for varying noise values and group sizes.[10] Load concentrations are decreasing in both, the number of groups and the noise level applied for creating randomized electricity rates. Given greater randomization, group rates will be less homogeneous which reduces load concentration. Similarly, more groups reduce the number of vehicles reacting to a specific rate. Interestingly, most of the peak load reduction potential can already be achieved with 50 groups.

[9] This part is also included in the working paper Flath and Gottwalt (2014).

[10] Note that randomized group pricing again leads to a stochastic simulation and results for this pricing regime are averaged over five simulation runs.

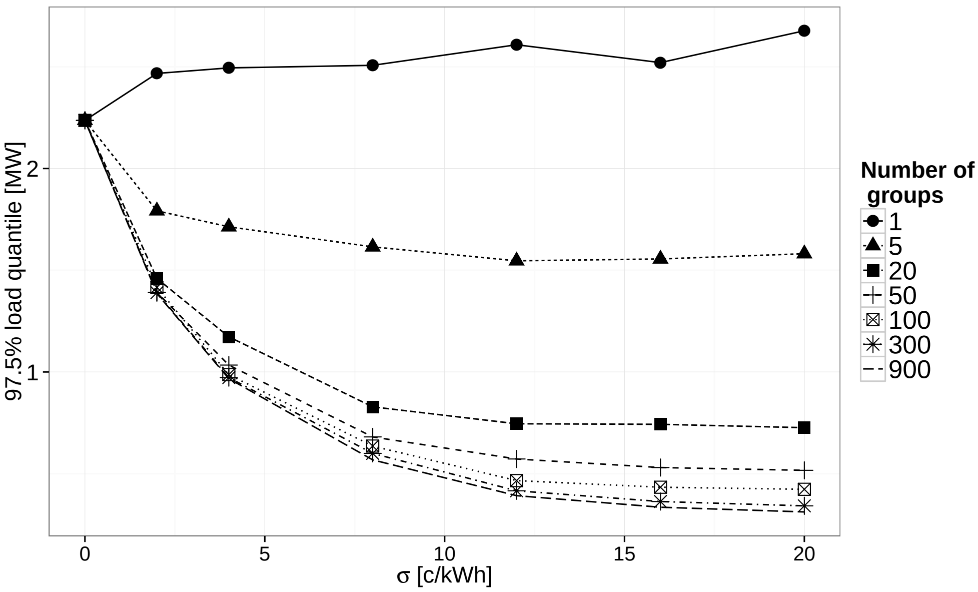


Figure 5.12: Effects of noise level for randomized rates and the number of groups on aggregate charging load (97.5 % quantiles)

Figure 5.13 depicts the average weekly conventional generation requirements over the simulation period. An interdependency between the number of groups and the rate randomization level can be observed: With a single group conventional generation usage is increasing in the rate randomization level. In this case, the random component dilutes the information on renewable generation availability, resulting in the same load concentrations as under RT pricing while ignoring availability of renewable generation. However, when moving to a larger number of groups some randomization is necessary to tap into the desynchronization potential of group pricing. For a smaller number of groups a low randomization level is optimal, else the information on available renewable generation will again be too diluted. For an increasing number of groups, conventional generation can only be further reduced if a stronger rate randomization (larger σ) is applied: Group rates become more distinct and coordination improves. Over a large number of groups the “average rate" will reflect the original RT price and the desired generation availability signal is retained. Well-chosen group pricing can hence ensure both a high coverage of loads by renewable generation while avoiding excessive load synchronization.

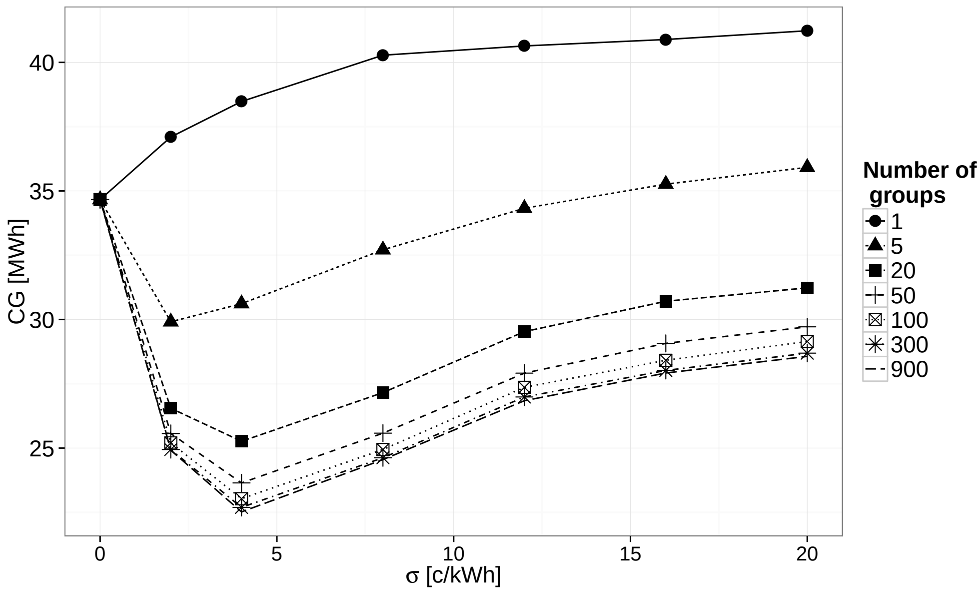


Figure 5.13: Effects of noise level for randomized rates and number of groups on conventional generation needs

5.6 Sensitivities of Group Pricing

Acknowledging the potentials of randomized group pricing an analysis for a more general model setting is carried out to derive insights for a greater number of real-world power systems . Therefore, the base scenario of the residential demand model with the full set of flexible devices is applied. As a reminder, the base scenario comprises 1,000 households, 160 EVs and 25 stationary batteries (see Table B.1 for the full specification). On the supply side another fluctuating decentralized renewable energy source (i.e., PV) is integrated as a basis for the retail rates . Due to the limitations of power-based surcharges for appliances with fixed load profiles, rates with surcharges are not included in this analysis.

Furthermore, this section focuses on the effect of reduced information availability as the evaluation under full information for one week has only limited practical relevance. Similar to the assessment of direct load control in the previous chapter, the indirect load control model is adapted to include day-ahead update of residential rates and uncertainty in renewable generation. Finally, the costs of decentralized coordination are discussed comparing group pricing (decentralized) and direct load control (centralized).

5.6.1 Generalized Evaluation Scenario

As mentioned before, for the application of group pricing three basic design decision have to be made. Hence, it is assumed that the number of groups (i) corresponds to the number of devices in the residential area and each group consists of one device (ii).[11] The rate for each group is determined by adding noise to the underlying RT rate (iii). For the standard deviation specifying the truncated normal distribution a value of $\sigma = 2$ is chosen. This low randomization level is due to the reduced system load. The base scenario has lower total system load as the simple model with 900 EVs and thus less renewable generation output. For the mapping of net renewable generation to retail rates less generation output reduces distances between price steps and a smaller randomization level achieves an appropriate desynchronization.

Figure 5.14 depicts mean values and standard errors for the weekly variable costs for group pricing in a residential area. As a reference also a flat tariff, RT pricing and the optimal benchmark under full information are depicted. Costs are normalized to the unresponsive load scenario under a flat tariff. In the figure it can be observed that RT pricing still results in the highest variable generation costs. In contrast to the previous analyses, RT pricing improves and performs only slightly worse than a flat tariff. This is even more surprising when considering the large share of flexible loads in the system. One reason for this improvement are the limitations in shifting distances of household appliances. EV charging can be scheduled over the course of the entire optimization week concentrating load in few times. The lower temporal flexibility of appliances often impedes shifting to the weekly price minima and thus avoids extreme peaks. However, to a smaller extent load synchronization still occurs. Group pricing greatly reduces variable generation costs as compared to a flat tariff. It effectively reduces synchronization and incentivizes shifting to make use of available renewable generation also in this more generalized evaluation setting.

[11] A large number of groups has shown the highest desynchronization potential. Pooling of devices to form groups on household or neighborhood level are other options for grouping.

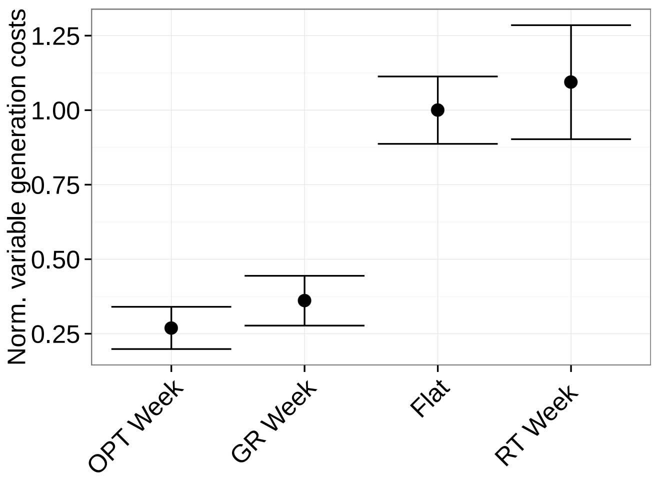


Figure 5.14: Normalized variable generation costs for the comprehensive model

5.6.2 Information Availability

To facilitate a more realistic day-ahead balancing, model alterations that enable daily update of electricity rates are presented. A reduction of the optimization horizon requires the application of a value for the left-over electricity θ for EVs and stationary batteries to retain inter-day flexibility (see Section 4.5.1). The resulting objective function for an individual stationary battery s is given by:

$$\min_{\phi_s} \sum_{t=1}^{T} p^t \cdot \phi_s^t - \theta_s \phi_s^T. \tag{5.10}$$

Under direct load control a storage value triggers charging only in hours with excess renewable generation. In contrast, price-based open-loop control requires a more careful analysis for the selection of an appropriate storage value. Each individual battery maximizes the revenue from charging and discharging under the respective price regime. To determine a meaningful value for the left-over electricity, distributional properties of the electricity prices are helpful. For stationary batteries population-wide price thresholds specified as quantiles of the simulation periods's price distribution are assumed. In addition, the availability parameter (a_s) to control charging and discharging activity influences the behavior of stationary batteries. For the availability quantiles of the price distribution are also used. Table 5.3 depicts the quantile levels that are applied for storage valuation and charging and discharging activity of stationary batteries under RT pricing and group pricing. The more restrictive thresholds for RT pricing reduce activity of stationary batteries and thus prevent load synchronization for this device. A sensitivity analysis which motivates the selection of the quantile values is provided in Appendix E.

Table 5.3: Quantile levels for storage valuation and charging and discharging activity of stationary batteries

Price Regime	Storage valuation (θ_s)	Charging threshold ($\underline{p}$)	Discharging threshold ($\overline{p}$)
RT	0.1	0.1	0.9
Group	0.2	0.2	0.8

For an individual electric vehicle the objective function including storage valuation is given by:

$$\min_{\phi_v} \sum_{t=1}^{T} p^t \cdot \phi_v^t - \theta_v \phi_v^T. \tag{5.11}$$

Similar to the stationary battery model, price quantiles are applied to determine valuation of the left-over electricity. For an individual EV the storage value has to balance between average SOC level and charging costs. For example, a high storage value results in high average SOC levels, at the same time a full battery might impede charging in low cost hours. Ideally, this price threshold is determined for each EV reflecting the driver's individual preferences. For the sake of simplicity, a population-wide storage valuation θ_v as a quantile of the simulation's price distribution is assumed. These values are fixed at the 0.1 quantile for RT pricing and at the 0.05 quantile for randomized group pricing. A sensitivity analysis of different quantile levels for left-over electricity valuation of EV charging is provided in Appendix E.

The storage valuation allows for daily optimization horizons and thus the integration of PV and wind forecasts for rate design. Figure 5.15 shows mean values and standard errors of the weekly variable generation costs for different optimization horizons and uncertainty in renewable generation. In addition to RT and group pricing, centralized control (OPT) and a static load scenario (Flat) are included. Latter serves as a reference where all variable generation costs are normalized to.

By comparing daily and weekly optimization horizons under full information in the left panel of the figure, it can be observed that a larger horizon slightly reduces variable generation costs for group pricing and the full information benchmark. However, for RT pricing weekly optimization increases variable generation costs. In this setting the devices with intra-day flexibility (i.e., EV and stationary batteries) often exploit daily price minima and reduce load concentration at the weekly minima. Daily optimization facilitates the application of renewable generation forecasts for rate design. The right panel of the figure shows that uncertainty in renewable generation deteriorates system efficiency under all coordination mechanisms. Yet, generation cost increase to a smaller extent for group pricing as compared to RT pricing.

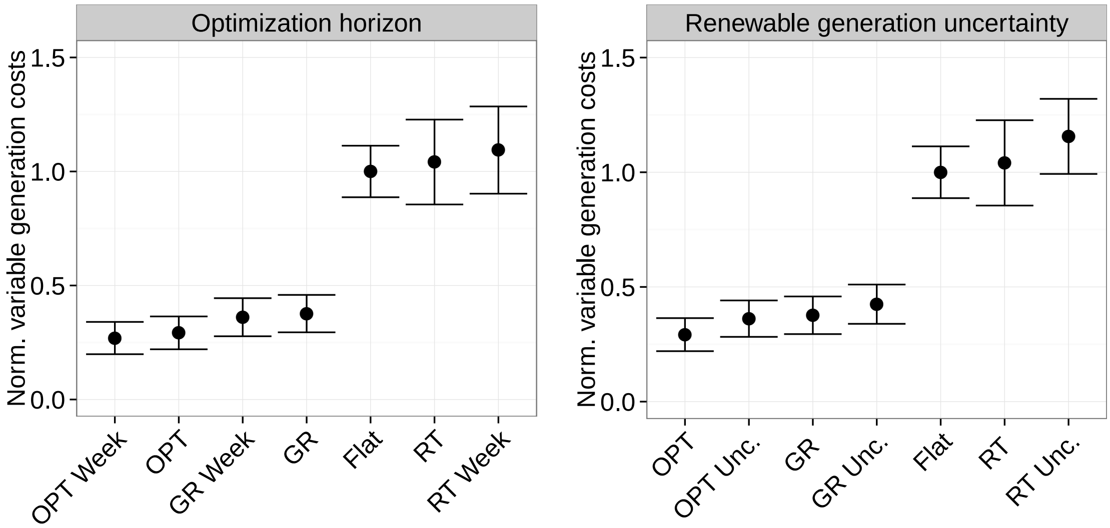
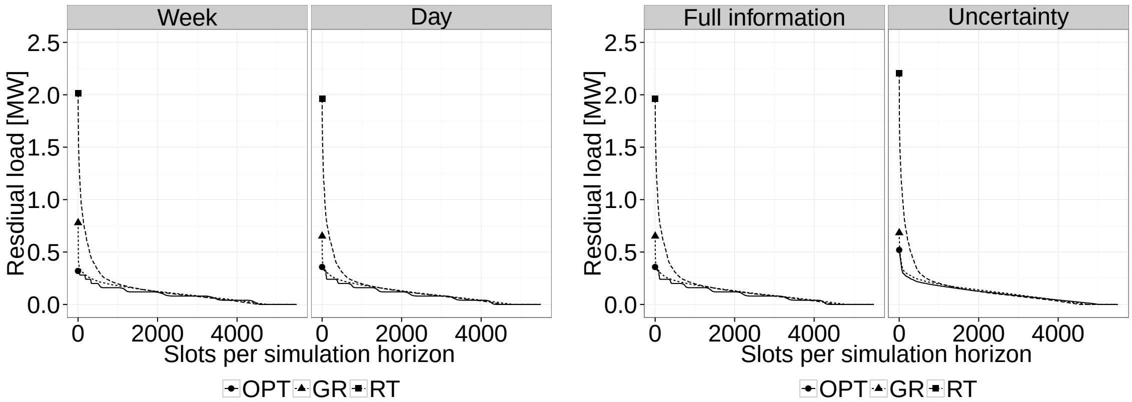


Figure 5.15: Normalized variable generation costs for different optimization horizons and uncertainty in renewable generation

For a better understanding of cost drivers residual load duration curves of one example simulation run are shown in Figure 5.16 for different optimization horizons and the effect of uncertainty in renewable generation. Overall, the most striking observation in the figure is the large reduction in peak load under group pricing as compared to RT pricing. This effective desynchronization of randomized pricing is not only visible in the peak value of residual load, but also for other slots with high loads. Meanwhile, for randomized pricing the load duration curve very well matches the optimal benchmark an increasing gap can be observed for the load duration curve of RT pricing for the 1,000 highest load slots. Thus, capacity requirements and total amount of conventional generation are at a low level for randomized group pricing.



(a) Optimization horizon (b) Renewable generation uncertainty

Figure 5.16: Residual load duration curves (Simulation horizon $T = 8064$ slots)

The left panel of Figure 5.16 shows slightly reduced residual load peak for a shorter optimization horizon under RT pricing. Thus, supporting the conclusion that a reduction in the weekly peak load is one factor for the decrease in variable generation costs considering a shorter optimization horizon.

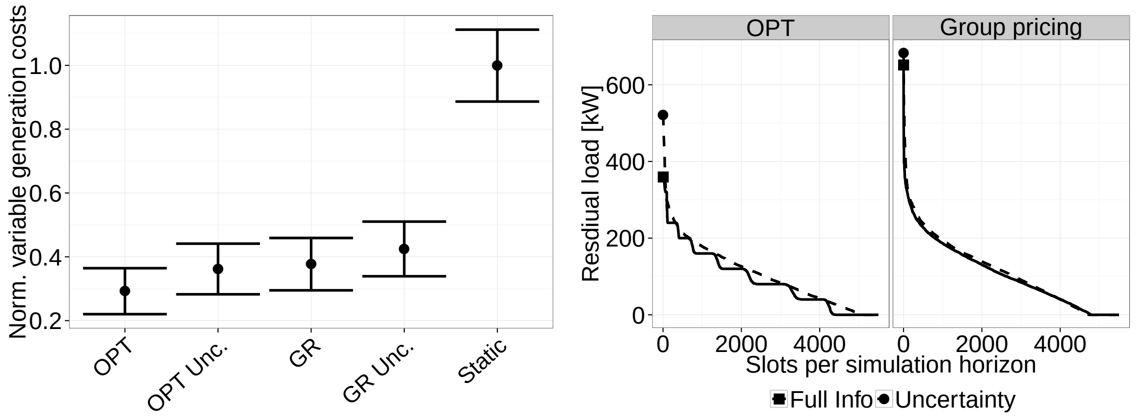
In the right panel of the figure it can be observed that uncertainty in renewable generation increases maximum residual load and consequently, conventional generation capacity requirements. The largest impact of uncertainty can be observed under RT pricing. High availability of renewable generation results in low retail rates and thus in a large synchronization of load. If generation in a period with load concentration is below the predicted level, large residual load values arise. Hence, load desynchronization also reduces the impact of uncertainty on residual load. This can be observed for group pricing, where the maximum residual load values under full information and uncertainty in renewable generation are very similar.

5.6.3 Costs of Decentralization

Decentralized decision regimes have lower computation and communication requirements and can retain customer privacy concerns compared to centralized control regimes. However, even when decentralized control regimes can improve power system operation they can not match the efficiency of centralized load control. In the following, the focus is put on the comparison of centralized (OPT) and decentralized (GR) control mechanisms from the previous evaluation. Therefore, variable generation costs and load duration curves for both control paradigms are analyzed to gain more insights in the costs of decentralized load control.

Figure 5.17a shows mean values and standard errors for the weekly variable generation costs of centralized (OPT) and decentralized control regimes (GR). The static load scenario (Flat) serves as a reference where variable generation costs are normalized to. Centralized control under full information establishes an upper benchmark for the potentials of flexible loads reducing variable generation costs to 29 % of the cost level under a flat tariff. Group pricing is able to exploit a large fraction of these cost savings reaching in average 38 % of the costs in the static scenario. Under uncertainty centralized control achieves less precise tracking of renewable generation and variable generation costs increase (36 %). Randomized group pricing is more robust under uncertainty and results only in a small cost increase (42 %). Thus, it can be observed that under uncertainty the gap between centralized and decentralized control regimes decreases.

The residual load curves in Figure 5.17b show in more detail the effects of optimal scheduling and group pricing when renewable generation forecasts are applied. Under full information centralized control exactly tracks the net renewable generation and if possible avoids scheduling beyond breakpoints of the piecewise linear function. The shape of the residual load, allows to identify the steps of the variable generation cost function. Uncertainty impedes precise renewable generation tracking and mismatches between realized generation and load schedule increases maximum residual load. For randomized group pricing fairly low changes in the load duration curve emerge and only a marginal increase in some residual load values can be observed.



(a) Normalized variable generation costs (b) Residual load duration curve ($T = 8064$)

Figure 5.17: Comparison of centralized (OPT) and decentralized (GR) control

5.7 Opportunities for Residential Households

To attain the benefits of dynamic rates customers do not necessarily have to be price responsive (Faruqui, 2010). For some residential households electricity generation can meet low price hours by chance and they will see a reduction in their bill before they adjust their consumption pattern. Flexible customers with the ability to adapt electricity consumption can achieve higher savings. However, as some (unflexible) customers encounter an increase in their electricity bill dynamic pricing often has to face the unfairness argument possibly posing a hurdle for its introduction. For randomized group pricing the perception of unfairness might be even more present. Subsequently, expected electricity bill savings of residential households due to flexible loads are analyzed and the fairness of dynamic electricity prices is discussed.

5.7.1 Electricity Bill Savings

Figure 5.18 depicts costs per kWh (left) and average weekly electricity costs per device (right) under RT and group pricing.[12] Data for this figure is obtained by executing a 12 week simulation of the indirect load control model with the base scenario. The price level of the flat tariff corresponds to the mean value of the RT rate. In the

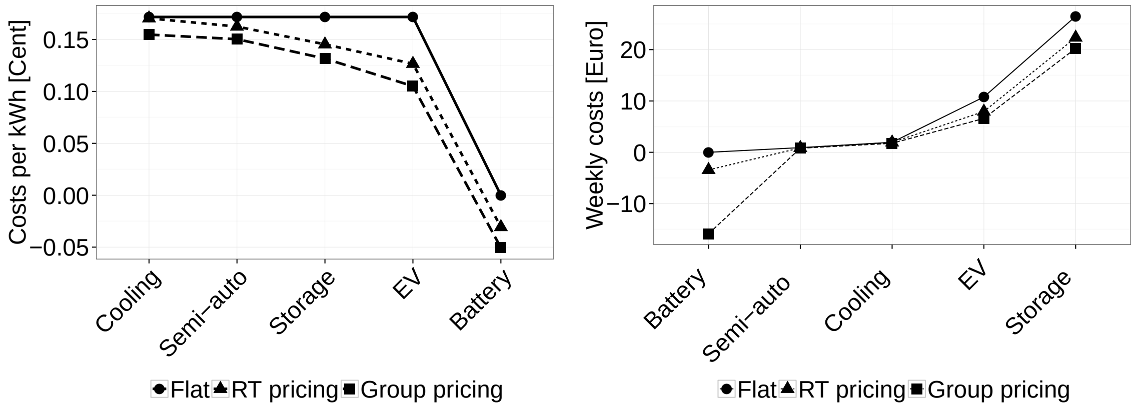
[12] Consumption costs of devices are illustrated as line charts to simplify the comparison between pricing regimes.

model electricity rates are created based on the availability of renewable generation and do not reflect retail electricity prices of German households. Electricity rates for residential customers in Germany comprise cost factors in addition to electricity provision, e.g., service fees for metering and billing (Ilg, 2014). Cost values in the subsequent analysis allow to compare effects of distinct price regimes. However, they do not represent electricity bill savings a household can expect.

EVs and storage heaters have large temporal flexibility for load shifting and often operate at hours with the lowest prices. As can be seen in the left panel of the figure they achieve low average costs per kWh. At the same time EVs and storage heaters are large loads and reach the highest reductions in electricity costs per device. Cooling and semi-automatically shiftable household appliances possess lower temporal flexibility. Consequently, they can realize only a small reduction in the per kWh costs. Due to their low consumption also weekly costs per appliance can only marginally be reduced. Stationary batteries generate revenues for residential households by charging in low price hours and discharging in high price hours.

Randomized group pricing achieves slightly lower costs per kWh and per appliance as compared to an RT rate. Group rates are determined by adding noise on the underlying RT rate. Flexible appliances can make use of these reduced prices. Despite similar costs per kWh the weekly revenues for stationary batteries largely increase under randomized group pricing. Load desynchronization under group rates allows a more frequent operation of stationary batteries without threatening power system efficiency. The more frequent charging and discharging activity leads to higher revenues per battery. Note that the spread of dynamic rates largely influences the economics of price-based load control (Gottwalt et al., 2011). Electricity cost savings for flexible devices and revenues for stationary batteries increase with higher spreads in a tariff.

The figure shows that customers with large and flexible appliances clearly benefit from dynamic pricing and can reduce their electricity costs. Yet, residential customers with unflexible loads might face a higher electricity bill as their static consumption coincides with high price hours. In particular, low-income customers with little load for shifting might be negatively affected resulting in a perception of unfairness for dynamic pricing (Faruqui, 2010). For randomized group pricing the perception of unfairness might be even more present.



(a) Costs per kWh

(b) Electricity costs per week and device

Figure 5.18: Cost reduction of flexible loads under RT pricing and randomized group pricing

5.7.2 Fairness of Dynamic Pricing

For a discussion of fairness aspects when introducing dynamic pricing the charging costs of EVs are analyzed in more detail.[13] EVs are ideal load for this analysis as the application of real-world driving profiles creates a heterogeneous fleet allowing to characterize key factors of demand response winners. Figure 5.19 illustrates the mean weekly charging costs and the standard error under RT pricing and randomized group pricing for the 160 EVs of the base scenario. Not surprisingly all EVs can reduce their charging costs as compared to a flat tariff fixed at the average value of the RT pricing rate (17.2 c/kWh). Under randomized group pricing EVs achieve lower average charging costs as compared to an RT rate. For both pricing regimes a broad range of average charging costs among the EVs can be observed.

To identify the key factors behind these cost differences, Figure 5.20 maps the average charging costs against the coefficient of variation.[14] Moreover, the size of the points represents the flexibility in EV charging calculated as ratio of charging amount per week to the number of periods where charging is possible. Large points indicate higher flexibility for charging. For both pricing regimes it can be observed that lower average charging costs can be reached by EVs with a higher flexibility. At the

[13]This section extends parts of our working paper Flath and Gottwalt (2014).

[14]Normalized measure for the variability of a frequency distribution. It is defined as the ratio between standard deviation and the mean.

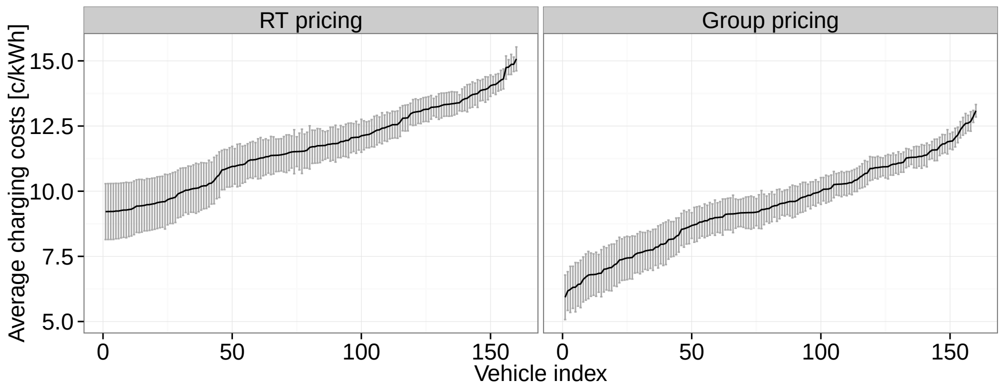


Figure 5.19: Average charging costs and standard error per vehicle under RT pricing and randomized group pricing

same time these EVs have a larger variation in their weekly costs. Under randomized group pricing flexible customers are able to achieve lower charging costs as compared to RT pricing. Hence, flexibility returns are even more pronounced. Note that due to the randomization on the short term one group of flexible customers might face higher rates, but on the long term the average price per kWh will approximate for all groups.

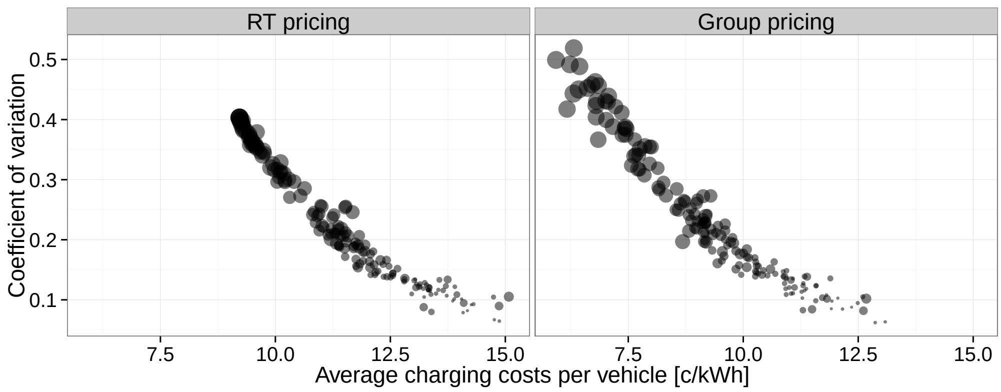


Figure 5.20: Average charging costs, coefficient of variation and charging flexibility of EVs (size of points) under RT pricing and randomized group pricing

Politics are one reason for the slow adaption of dynamic pricing as the state aims to "protect retail customers from the vagaries of competitive markets" (Hirst, 2001). A common argument is that dynamic pricing might increase electricity bills of low income customers. In this discussion Faruqui (2010) argues that the "presumption of unfairness in dynamic prices rests on an assumption of fairness in today's tariffs". A flat tariff with a constant price level creates a cross-subsidy between unflexible and flexible customers. Dynamic pricing achieves an improved coupling between costs and prices and reduces cross-subsidies inherent in flat rates. DR increases the number of winners under a dynamic pricing scheme and as shown by Figure 5.20 electricity costs decrease with customer's flexibility. Since group pricing avoids herding and increases load coverage, it results in a more efficient system operation and thus allows for lower average retail prices for all customers. Therefore, also inflexible customers might benefit from price-based demand response. For RT pricing this reasoning only holds for a small share of flexible loads in the system, where power system efficiency is improved. For a large share of flexible loads degrading system efficiency can increase retail prices. Hence, only the most flexible customers might be better off and a large share of residential customers might encounter an increasing electricity bill.

Low-income customers in general have a smaller set of appliances and thus might not be part of the most flexible customers. Nevertheless, in a field test they showed a high responsiveness to DR incentives (Wolak, 2010). These price responsive low-income customers can also expect at least moderate benefits from group rates. If still some low income customers might face a higher electricity bill, increasing system efficiency creates potentials for transfer payments.

5.8 Discussion

Recent research has been somewhat pessimistic concerning the potentials of price-based coordination for DR due to the occurrence of load synchronization effects.[15] This chapter presented an indirect load control model to explore DR effects under different electricity rates. Using EV charging as an example it can be shown that standard RT pricing, typically a posted price scheme with fluctuating but reliable price levels, improves power system efficiency merely in the presence of minor penetration levels of flexible loads.

[15]The discussion comprises some parts of our working paper Flath and Gottwalt (2014).

Starting from regular RT and TOU pricing approaches, it is argued that modifications of these rates can reduce load synchronization effects even in a system with a high share of flexible loads. This motivates the introduction of rate desynchronization approaches. First, a power-based surcharge that induces more distributed charging behavior is presented. Furthermore, individualization of residential electricity rates is proposed and implemented in form of group tariffs. For group pricing a three step approach for implementation is established: (i) determine the number of different groups, (ii) assign customers to groups, and (iii) specify a rate for each group. Using an example driven-style it is shown that the rate modifications can greatly reduce over-coordination of flexible loads and conventional generation requirements.

For a comprehensive assessment of the retail rates and their modifications the analysis is extended and the stylized power system model penalizing both total amount and high concentrations of conventional generation is applied. Results indicate that these rate modifications successfully help to decrease variable generation costs. They reduce load synchronization and thus costly peaks of conventional generation and increase overall load coverage with RES by limiting the extreme reliance on times of high renewable generation.

To better understand the application of the desynchronization approaches, a more detailed analysis to determine design guidelines for implementation is provided. The power-based surcharge is in principle an effective means. However, if the surcharge level is too high the price incentive indicating renewable generation availability is diluted and system efficiency decreases. Furthermore, a power-based surcharge entails some limitations for real-world application as temporal flexibility of electric appliances with a fixed load profile can not be exploited. Moreover, power surcharges might induce inefficiencies when individual consumption is penalized in uncongested situations. For the performance of group pricing the randomization level and the number of groups are the most important influence factors. The simulation results indicate that for smaller number of groups a low randomization level is optimal, else the information on available renewable generation will be too diluted. For an increasing number of groups, conventional generation can only be reduced if a stronger rate randomization is applied: Rates of groups become more diverse and coordination improves.

Given the potentials of group pricing, a more generalized evaluation setting is applied including a mixed renewable generation portfolio (PV and wind) and the full set of flexible residential devices. This analysis shows that the randomization level for group pricing depends on the underlying price structure and that the temporal flexibility of devices is a crucial driver for load peaks. With respect to the availability of information, the simulation results indicate that a reduced optimization horizon has only marginal impact on system efficiency. In addition, it can be observed that under uncertainty in renewable generation system efficiency for group pricing only slightly deteriorates.

For electric utilities centralized control is attractive due to the reliable behavior of each individual unit. Yet, scalability and privacy issues may impede large applications. The analyses reveal that decentralized control instantiated via RT pricing deteriorates system efficiency and performs worse than unresponsive load under a flat tariff. In contrast, group pricing achieves large reductions in variable generation costs and the theoretical cost reduction potentials established by the optimal benchmark can be exploited to a great extent. Uncertainty in renewable generation deteriorates system efficiency of centralized and decentralized regimes. Yet, randomized group pricing is more robust under uncertainty and the gap between centralized and decentralized control shrinks.

Finally, the focus of the evaluation has been put on the opportunities of price-based load control for residential households. Here, large and flexible devices (i.e., EVs, storage heaters and stationary batteries) have been demonstrated to provide the largest benefits. Further, results suggest that group pricing does not give rise to fairness issues compared to standard real-time pricing or a flat tariff. Under group pricing benefits of customers increase with their flexibility bearing down the prevailing cross-subsidies of flat rates. Moreover, improving overall system efficiency can lead to lower system costs and allows lower average retail electricity rates for all customers.

5.8.1 Limitations

The presented coordination approaches have limitations which are discussed in this section. For the simulations retail electricity rates are built on a renewable generation forecast and transmitted to the residential devices which individually optimize their operation schedule. However, in a smart grid an electric utility might rather send signals to a building management system than to individual appliances. Such a management system might obey objectives beyond sole cost minimization of device operation, e.g., maximum usage of self-generated electricity. Also additional decentralized energy resources (e.g., combined heat and power plants) and storage systems (e.g., water storage tanks) are likely to be available in modern buildings. Thus, coupling thermal and electrical energy generation offers broad flexibility for in-house optimization of energy usage (Mauser et al., 2014). Building management systems maximizing usage of self-generated electricity and controlling a wide set of generation and storage technologies in one household can influence the system effects of price-based load control.

Further, electricity cost savings for residential devices are based on artificial electricity rates which reflect the available renewable generation. Undeniable, these savings are a snap-shot driven by the underlying retail rates. Hence, the cost numbers allow to compare the performance of residential devices under dynamic pricing and to identify characteristics of promising devices. However, the absolute cost values have low explanatory power. Applying attributes of current spot prices and additionally integrating fees and taxes can help to get a more realistic estimation of saving potentials for devices. Another option might be to vary the characteristics of electricity rates (e.g., volatility or price level) to get deeper insights into the effects of rate structures on the economics of dynamic pricing for individual households.

Similar to the limitations of direct load control (see Section 4.7.1) an oversimplified system is employed for the evaluations presented. Therefore, the discussed model extensions on demand and supply side can also improve generalization of results for price-based DR. Especially physical grid constraints may pose additional limitations for the adoption of group pricing. Dauer et al. (2014) present a case study for the application of group pricing in an exemplary local distribution grid. In a simple scenario they illustrate that group pricing can desynchronize load on a local level and avoid load cut-off by the system operator to prevent transformer or line overloads. Yet, to ensure robust results a more comprehensive analysis of different distribution grid structures is required in future. To adhere local grid constraints it might be required to combine group pricing with other mechanisms, e.g., revenue management approaches to allocate transformer capacity (Flath et al., 2012).

5.8.2 Future Opportunities

The analysis of price-based load control gives rise to subsequent research questions. The proposed rate modifications reduce variable generation costs, however, to achieve a fully reliable balancing a tariff based control would have to be combined with other control options (Heussen et al., 2012). For this purpose, e.g., direct control of large industry loads can complement a flexible residential load portfolio.

On the consumption side, the flexibility of a device is independent of the price level. It would be interesting to connect this flexibility with the savings a customer can realize by price-based operation scheduling. Further, research needs to focus on eliciting load shifting potentials and customer preferences of residential households in future field studies. Based on such richer data sets, bottom-up household models can be validated and enhanced using real-world experiences for parameter calibration. Moreover, participation constraints on behalf of the customers can reduce the effectiveness of coordination mechanisms and result in supplementary costs (e.g., contracting). This could be addressed by using mechanism design principles or considering varying participation levels.

With a broad set of flexible devices, group composition for randomized prices might become important as customers can be segmented according to their energy needs or the flexibility they provide. Thus, an advanced group pricing procedure might improve system performance. Extending customer segmentation by a load flow analysis can further improve understanding of spatial distribution of flexible customers on power system stability and guide customer segmentation according to the grid structure.

In analogy to the direct load control, a yearly simulation horizon to integrate seasonal variations in household demand and renewable generation patterns renders more general conclusions just as an expansion of the device set and penetration levels to typical values of other countries (see Section 4.7.2).

Chapter 6

Conclusion

This thesis focuses on the effects of an active demand side in the operation of future power systems. Therefore, an appropriate modeling approach for demand flexibility and generation provision is developed. The model is then applied to assess DR potentials of direct load control under incentive-based programs and to analyze different coordination mechanisms for a more efficient operation of the power system. The discussion sections for flexibility potential of residential loads (Section 4.7) and for the coordination mechanisms (Section 5.8) list limitations and opportunities for future research. This conclusion summarizes main implications from the previous chapters and thus provides a consolidated overview of the key findings addressing the research questions put forward in Chapter 1. Finally, an outlook on the most important challenges for future work and open questions to enable the smart grid vision is provided.

6.1 Summary

The promotion of renewable energy sources leads to fundamental transformations in the electricity sector. In such a power system an active participation of the demand side is a promising approach to improve load balancing. Flexible loads in residential areas are mainly untapped today. ICT technologies in a smart grid facilitate coordination of a large number of these small loads offering potentials for balancing in a system with a large share of renewable generation.

Chapter 2 provides an overview of the main functions along the traditional electricity value chain (generation, transmission, distribution, and consumption) and summarizes ongoing transformations and future challenges in system management. Moreover, it describes the idea of a smart grid for future system operation and depicts the benefits of flexible loads.

Given the importance of an accurate representation of customer reaction and power system for an assessment of DR effects, Chapter 3 introduces a simulation framework comprising demand and supply components. Using a structured approach for customer modeling, the bottom-up models for demand flexibility of household appliances, stationary batteries and EV charging are described. For each model a discussion of its basic properties, input data for calibration, demand response characteristics, and a formalized consumption model are provided. Suitability of household appliances for shifting are assessed according to the effect of DR on customer's convenience. Fridge, freezer, and storage water and space heaters possess a natural thermal storage. Electricity usage and service provision can be decoupled and they can be controlled automatically without noticeable differences in utility for household members. Operation of washing machine, dishwasher, and tumble dryer can be started automatically, but require interaction with users. Residents set them into a ready mode and specify a flexibility interval in which an operation can then start automatically. Other household appliances are not-controllable in the demand model. Either they are not suitable for shifting or are of limited importance in Germany.

Moreover, this chapter analyzes the main output characteristics of renewable generators emphasizing their short term volatility by illustrating rapid changes in output levels for PV and wind. However, this analysis also shows seasonal or yearly variations in renewable generation output which can not be addressed via residential DR. Furthermore, the stylized power system model with a large share of renewable generation and additional conventional generation capacities is described.

Residential households in a DR program adapt their electricity consumption through direct load control or price-based incentives (Albadi and El-Saadany, 2008). Chapter 4 focuses on the synergies an aggregator achieves through directly controlling flexible loads to balance volatile renewable generation. The active participation of loads affects decisions of the aggregator on different levels. Dispatching of flexible loads (operational level) can greatly increase load coverage by renewable generation. Yet, day-ahead scheduling based on renewable generation forecasts gives rise to hours with high uncovered loads. This calls for improved forecasts of renewable generation or shorter optimization horizons with more frequent rescheduling of loads. For demand planning in the portfolio (tactical level) the simulations demonstrate that batteries, EVs, and storage heaters are the most promising residential devices for balancing. Aggregators with the need for demand flexibility should aim for contracting these devices. In the long run an aggregator decides on investments in renewable generation capacities (strategic level). The analysis of different wind and PV capacities in the portfolio indicates that benefits of DR arise beyond renewable generation shares covering 50 % of total load. Below this level hardly any improvements can be achieved through DR. With respect to the supply mix, an equally balanced wind and PV portfolio leads to the lowest procurement costs for the aggregator.

For providing flexibility to an aggregator residential households receive incentive payments. More flexible customers can expect higher compensations. Mapping the variable generation costs to individual appliances indicates that EVs, stationary batteries, and storage heaters have the largest cost reduction potentials. Residential households with such a device can benefit most from participating in DR programs. Furthermore, devices in a residential area allow to derive key features characterizing demand flexibility. The evaluation on device level suggests that the capacity to adapt—in this study the potential for load balancing— is mainly driven by electricity consumption and shifting distance of a device. The restrictions for scheduling are of minor importance.

In Chapter 5 different coordination mechanisms for controlling a large number of small flexible loads are investigated. Particularly, price-based coordination is in the center of attention. The results show that under automated demand response basic open-loop rates (e.g., RT or TOU pricing) are appropriate for coordinating small shares of flexible loads. In systems with large flexibility they lead to herding effects and deteriorate efficiency. This motivates the introduction of two approaches to mitigate the over-coordination phenomenon. Firstly, a power-based surcharge is presented which induces a more distributed charging behavior. Secondly, group tariffs are proposed to achieve an individualization of residential electricity rates.

Under this price regime customers are assigned to groups and all members of one group receive the same rate. The analyses demonstrate the improvements in power system operation for both approaches. They reduce load synchronization and thus costly peaks of conventional generation and increase overall load coverage with renewable generation. However, a more detailed investigation shows some limitations for real-world application of power-based surcharges, e.g., they penalize in uncongested situations and are not appropriate for devices with a fixed load profile.

The promising results of group pricing are confirmed in an ample simulation setting including a broad range of flexible devices. To create the group-specific prices, noise is added to an underlying RT rate. For the implementation of group prices the simulation results show noise level and number of groups as the most important influence factors. Higher noise levels are required for an increasing number of groups and larger spreads in the underlying RT rate. Furthermore, the evaluations indicate that under uncertainty in renewable generation group pricing is rather robust and can exploit a large share of DR potentials established by an optimal benchmark. Thus, instantiating decentralized control with group pricing demonstrates rather low cost of decentralization. Moreover, the simulation results suggest that group pricing does not give rise to fairness issues as benefits of customers increase with their flexibility resolving the cross-subsidies of current flat tariffs.

Reforming electricity pricing is an important task for regulators faced with the integration of high levels of RES.[1] While adaptive prices may achieve higher coordination efficiency than open-loop posted prices, they may lack of customer acceptance and their implementation may tend to failure (Dütschke and Paetz, 2013). Hence, closed-loop adaptive pricing remains a somewhat distant vision in retail markets. In the short and medium term, regulators should hence try to promote dynamic yet reliable price signals. Group pricing as presented in this section extends today's control of storage heaters in residential households, where grid operators determine groups of storage appliances and transmit intervals on group level to desynchronize these large loads (Hastings, 1980). Smart grid technologies facilitate easy and effective grouping of customers. Hence, such a scheme provides a promising control

[1] The paragraphs on policy recommendations for reforming electricity prices and the example application of randomization are also part of our working paper Flath and Gottwalt (2014).

option in retail electricity markets. Furthermore, adapting group pricing would not expose customers to price nor quantity risk and at the same time energy suppliers would retain the possibility of coordinating flexible loads.

An example for a successful application of randomization is given by the recent practice of “opaque selling” (Fay, 2008). Here, an intermediary offers a generic product (e.g., “4-star-hotel in Rome”) to a customer. The concrete realization, e.g., Hilton vs. Marriot vs. Intercontinental) is not published at the time of sale. The introduction of randomness allows higher capacity utilization and profitability for providers. On the other hand, customers can make a bargain.

6.2 Outlook

The electricity sector in Germany and other countries is undergoing fundamental changes. Increasing shares of renewable energy sources conflict with the existing power grid control infrastructure posing challenges to system operation. ICT infrastructure for observing and controlling power system components together with a software layer enabling novel applications and business cases pave the way for a new vision of power system operation—the smart grid. Such a future system consists of a large number of different actors with the ability to actively participate in system operation. To this end, multiple ideas to organize and control these actors are discussed. This thesis puts the focus on two different concepts. Firstly, direct load control of flexible loads by an aggregator to balance renewable generation in one portfolio is analyzed. Secondly, price-based demand response programs are revisited to illustrate limitations and provide novel solutions.

The smart grid affects various research disciplines and gives rise to a great number of challenges. A selection of open questions on the way to a smart grid is given subsequently. A future smart grid will be composed of heterogeneous components *and* organizational concepts: Building automation systems combine devices on customer level and create prosumers that can be an active part of the grid. Virtual power plants bundle generators and consumers to sell or buy electricity as an aggregate. Demand response can offer control potentials by the active coordination of flexible loads. An interesting opportunity for future research is the interaction of these different concepts to organize smart grid actors. Combining virtual power plants, demand response, prosumers, and other concepts might greatly improve efficiency of power system operation.

Additionally, the integration of the underlying physical power grid in future analysis is important to better understand opportunities and risks of a smart grid. For example, local distribution grid constraints might prohibit an electric vehicle to comply with its commitments to provide operating reserve in a vehicle pool. Therefore, a power flow analysis incorporating losses, line utilization, voltage, and transformer utilization is required to address interdependencies between different organizational concepts in the smart grid and to identify limitations due to infrastructure. Load flexibility offers considerable potentials for demand and supply balancing in a system with a large share of intermittent renewable generation. However, this only holds for short term variations in renewable generation output. Seasonal characteristics of wind and PV can lead to large over- and undersupply in some weeks or month. In such a power system load flexibility should be complemented by long term storages, e.g., power to gas or compressed air.

In addition to technical aspects, other impact factors are of importance to realize the smart grid vision. Economic incentives guide potential smart grid actors and will after all decide on their participation. The investment in ICT infrastructure can facilitate a broad range of smart grid applications. Yet, revenues from a single application today hardly covers these initial investments and (temporary) regulatory support to attract capital expenditure might be required.

A crucial role in the transformation to a smart grid comes up to the individual citizens. A large number of individuals investing in small generators enabled the high share of renewable generation for electricity provision in Germany. Similar, participation of citizens and thus customer acceptance of technical and economical solutions is key to integrate decentralized generation units and flexible loads in a smart grid.

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Appendix A

List of Abbreviations

AFAP	As Fast As Possible Charging Strategy
BDEW	Federal Association of Energy and Water Industries
CG	Conventional Generation
CHP	Combined Heat and Power Plant
CPP	Critical Peak Pricing
DR	Demand Response
DSM	Demand Side Management
DSO	Distribution System Operator
EU	European Union
EV	Electric Vehicle
GR	Group Pricing
HL	High-Low Pricing
HVAC	Heating, Ventilation or Air-Conditioning
ICE	Internal Combustion Engine
ICT	Information and Communication Technology
IEC	International Electrotechnical Commission
OECD	Organization for Economic Co-operation and Development
PHEV	Plug-in Hybrid Electric Vehicle
PV	Photovoltaic
RES	Renewable Energy Sources

RG	Renewable Geneation
RT	Real-Time Pricing
SOC	State-Of-Charge
TOU	Time-Of-Use
TSO	Transmission System Operator
V2G	Vehicle-to-Grid
VPP	Virtual Power Plant

Appendix B

Centralized Control Model

Table B.1: Base case specification

	Parameter	Base Case	Unit
Simu-lation	Number of weeks	12	
	Optimization horizon	672	15-min. steps
	Number of Runs	5	
Demand side	Number of households	1,000	households
	Number of EVs	160	vehicles
	EV battery capacity	30	[kWh]
	Charging power EV	11	[kW]
	Vehicle consumption	0.15	[kWh/km]
	EV initial SOC = end SOC	30	[%]
	Charging possible	Home&Work	
	Stat. battery capacity	7	[kWh]
	BAT charging/discharge power	4	[kW]
	BAT initial SOC = end SOC	30	[%]
Supply side	Scale renewable generation	100	% of demand
	PV share on RES	50	[%]
	Wind share on RES	50	[%]
	CG capacity	4,000	[kW]
	Variable generation costs step size	40	[kW]
	Cost increase per step	2.5	[Monetary unit]

Listing B.1: ILOG OPL optimization program for centralized scheduling of semi-automatically controlled appliances

```
/*Parameters*/
int NbPeriods = ...;
range Periods = 1..NbPeriods;
int NbGenerationSteps = ...;
float NetResGeneration[Periods]=...;
float maxConventionalGeneration = ...;
float slope[1..NbGenerationSteps+1] = ...;
float breakpoint[1..NbGenerationSteps] = ...;
int NbDurationSemiAuto = ...;
range DurationSemiAuto = 1..NbDurationSemiAuto;
int NbRunsSemiAuto = ...;
range RunsSemiAuto = 1..NbRunsSemiAuto;
float ProfileSemiAuto[DurationSemiAuto]=...;
float StartIntervalSemiAuto[RunsSemiAuto][Periods]=...;

/*Decision variables*/
dvar int OptimalStartSemiAuto[RunsSemiAuto][Periods] in 0..1;
dvar float+ CG[Periods];

/*Objective function*/
minimize
sum(t in Periods )(piecewise(i in 1..NbGenerationSteps)
{slope[i] -> breakpoint[i];slope[NbGenerationSteps+1]} CG[t];

subject to {
/*Power system constraints*/
forall(t in Periods)
ctConventionalGenerationCapacity:
CG[t]<=maxConventionalGeneration;
```

```
forall(t in Periods)
ctNonNegativeCG:
CG[t]>=0;

forall(t in DurationSemiAuto)
ctSystemBalanceBeginningHorizon:
CG[t] + NetResGeneration[t]
− sum(r in RunsSemiAuto, i in 1..t)
(OptimalStartSemiAuto[r][t+1−i] ∗ ProfileSemiAuto[i]))>=0;

forall(t in DurationSemiAuto..NbPeriods)
ctSystemBalance:
CG[t] + NetResGeneration[t]
− sum(r in RunsSemiAuto, d in DurationSemiAuto)
(OptimalStartSemiAuto[r][t+1−d] ∗ ProfileSemiAuto[d]))>=0;

/∗Device constraints∗/
forall(r in RunsSemiAuto)
ctStartSemiAuto:
sum(t in Periods)OptimalStartSemiAuto[r][t]>=1;

forall(r in RunsSemiAuto)
ctStartSemiAuto2:
sum(t in Periods)OptimalStartSemiAuto[r][t]<=1;

forall(r in RunsSemiAuto, t in Periods)
ctStartOperationInFlexibilityInterval:
OptimalStartSemiAuto[r][t] <= StartIntervalSemiAuto[r][t];
};
```

Appendix C

Output Data Analysis for Stochastic Simulation

A seminal work addressing simulation modeling and analysis is due to Law (2011). For the output data analysis of stochastic simulations he posits a sequential procedure to estimate the number of replications required for meaningful results. As a basis for this procedure, subsequently, it is shown how to derive a point estimation and a confidence interval for the mean of stochastic simulation output. Further, Law's procedure to derive the number of replications is explained and employed for the residential household model. This section contains an aggregate of Law's remarks and an application of his procedure on the presented model.

Estimating Means

For a terminating stochastic simulation let X_j be a random variable from making $j = 1, 2, \ldots, n$ simulation runs. Realizations X_j for runs are not the same as they use different samples from the input probability distributions for running the simulation. Law (2011) states that the two realizations of the random variables X_j are independent and identically distributed. The independency across runs is the key for the output data analysis he provides. An approximate $100(1 - \alpha)$ percent with $0 < \alpha < 1$ confidence interval for the point estimate of the mean $\mu = E(X)$ of n independent replications of the simulation is given by:

$$\overline{X}(n) \pm t_{n-1,1-\alpha/2}\sqrt{\frac{S^2(n)}{n}}, \tag{C.1}$$

where $\overline{X}(n)$ and $S^2(n)$ are the sample mean and variance and α.

Approximate Confidence Interval

The confidence interval is called approximate since the correctness depends on the assumption that the X_j's are normally distributed which will be rarely satisfied in practice. However, for experiments where the precision of the confidence interval is not "overwhelmingly important", the proposed estimation of sample mean and confidence interval brings acceptable results. Only with X_j's that are highly nonnormal and a very small number of replications n, the coverage of the calculated confidence interval may be low. In the work at hand the estimation of variable conventional generation costs is the major objective. Figure C.1 shows the histogram for this costs based on 1,000 replications of a population with 1,000 residential households for static household load (Static) and centralized load control (OPT).

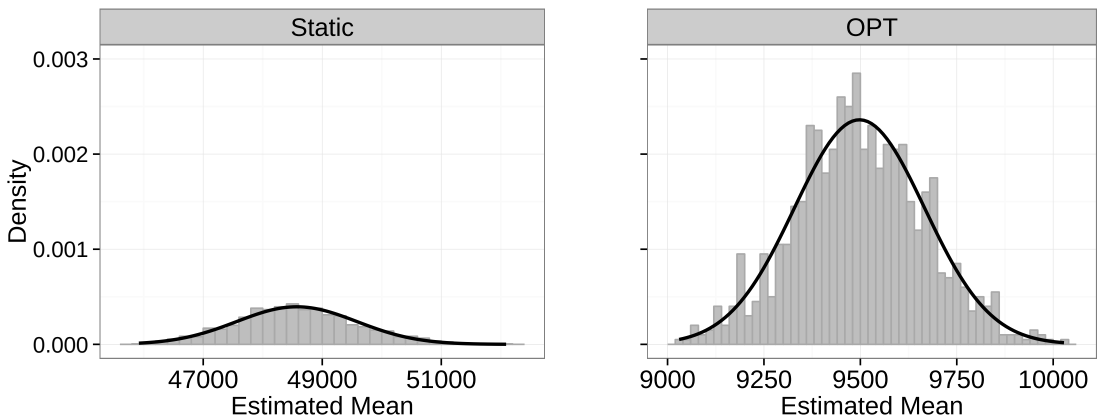

Figure C.1: Histograms and normal distribution for the estimated mean variable generation cots ($n = 1,000$) of one day

The sample skewness is 0.18 for the static scenario, respectively 0.06 for the centralized load control, thus close to the non-skewed normal distribution. Hence, for the variable conventional generation costs the assumption of normality seems not to be farfetched.

Precision of Mean

To estimate the mean $\mu = E(X)$ with a specified error a number n of simulation replications is required. The relative error γ of the estimate $\overline{X}$ is given by $|\overline{X} - \mu|/|\mu| = \gamma$. As μ is estimated by $\overline{X}$ the relative error is $\gamma' = \gamma/(1-\gamma)$ rather than the desired γ. To obtain an estimate of μ with a relative error γ' and a confidence level of $100(1-\alpha)$ percent with $0 < \alpha < 1$ the following procedure of Law (2011) is applied:

1. Make $n_0 \geq 2$ initial replications of the simulation and set $n = n_o$.
2. Compute $\overline{X}(n)$ and $\delta(n, \alpha)$ for the random variables X_j with $j = 1, 2, \ldots, n$, where the confidence-interval half-length is defined by:

$$\delta(n, \alpha) = t_{n-1,1-\alpha/2}\sqrt{S^2(n)/n}. \tag{C.2}$$

3. If $\delta(n, \alpha)/|\overline{X}(n)| \leq \gamma'$, stop and use $\overline{X}(n)$ as the point estimate for μ. Else, make another simulation run, replace n by $n+1$, and go to step 2.

As a result the interval $I(\alpha, \gamma) = [\overline{X}(n)+\delta(n, \alpha), \overline{X}(n)-\delta(n, \alpha)]$ is an approximate $100(1-\alpha)$ percent confidence interval for μ with the desired precision γ. In other words, for 100 independent 95 percent confidence intervals calculated with Law's procedure (each interval based on n replications) in about five cases the relative error is expected to be greater than γ'.

In the household load simulation the estimation of variable conventional generation costs is one major objective. Figure C.2 shows the effect of the number of simulation replications on the relative error (precision) of the estimated mean costs. The values have been obtained by following Law's sequential procedure performing an additional simulation run for each iteration. In the figure it can be observed that already a limited number of replications n results in a low relative error. For a one day simulation of 1,000 households with $n = 5$ replications the relative error is 3 %, respectively about 1.5 % for a simulation horizon of one week. Thus, increasing the simulation horizon and estimating the mean on more observations reduces the relative error. Two main aspects for the high precision with limited replications can be identified. First, in the residential household model merely starting times of appliances are random variables. Further, with a population size of 1,000 households effects of stochastic inputs are averaged out.

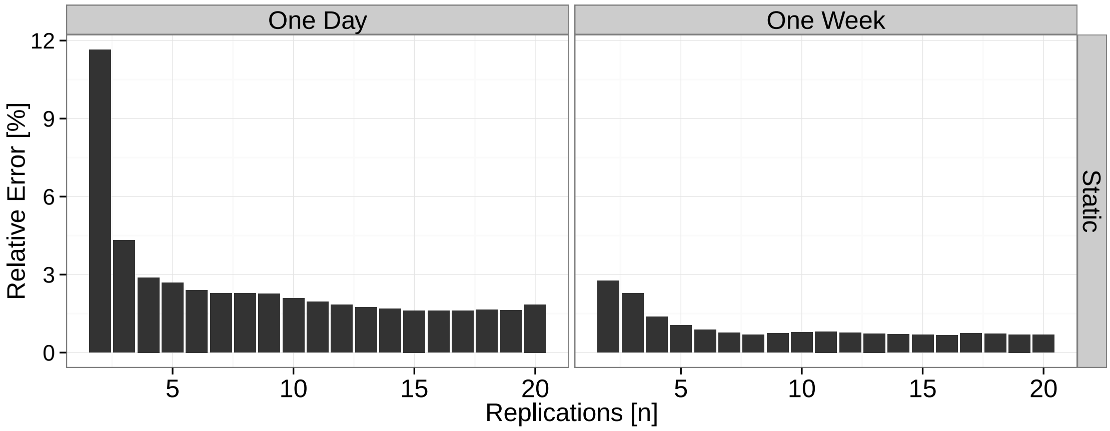

Figure C.2: Effect of number of replications on the relative error

Note that only the residential household model uses probability distributions. Considering deterministic EVs and stationary batteries further decreases the impact of stochastic inputs on the estimation of variable generation costs. Law recommends making at least three to five replications of a stochastic simulation to achieve valid estimations of the evaluation parameters. Due to the limited impact of stochastic inputs and the resulting low relative errors, parameter estimations in this thesis are based on five replications of the stochastic residential household model.

Appendix D

Load Profiles on Device Level

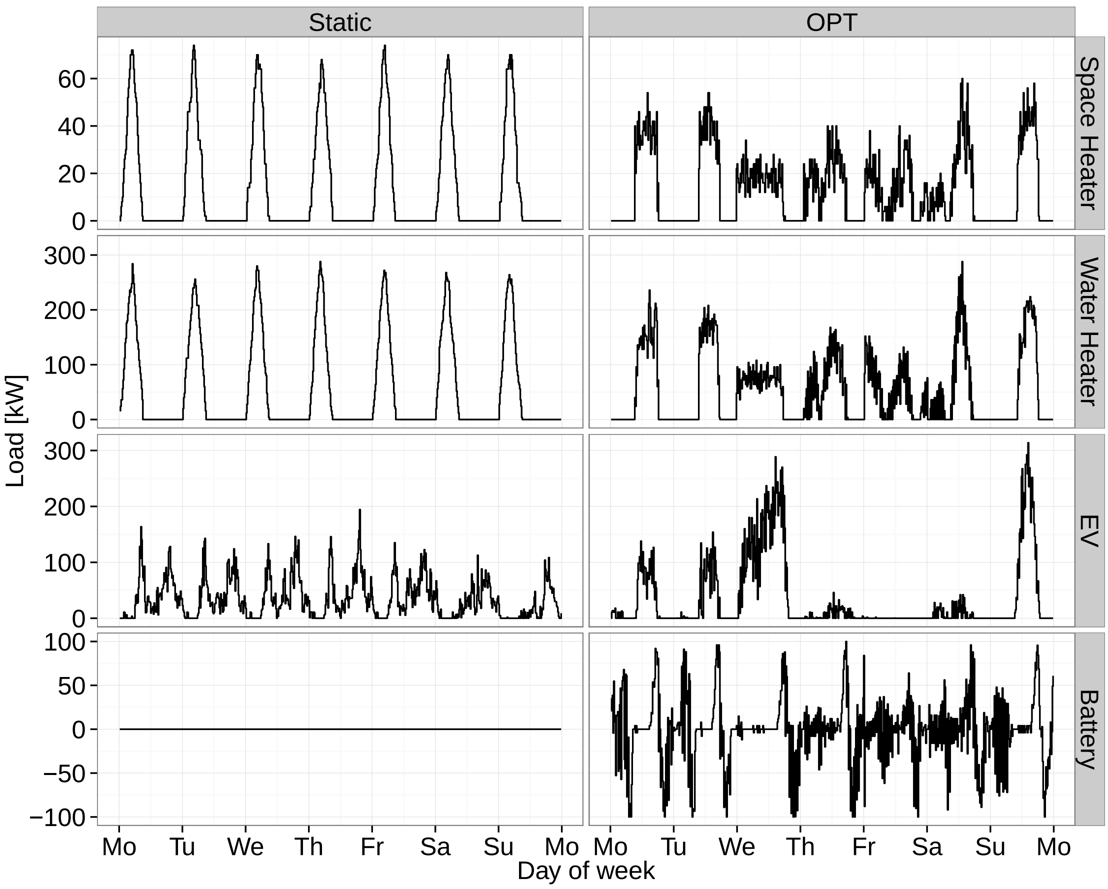

Figure D.1: Load for uncontrolled (Static) and controlled (OPT) devices over one week

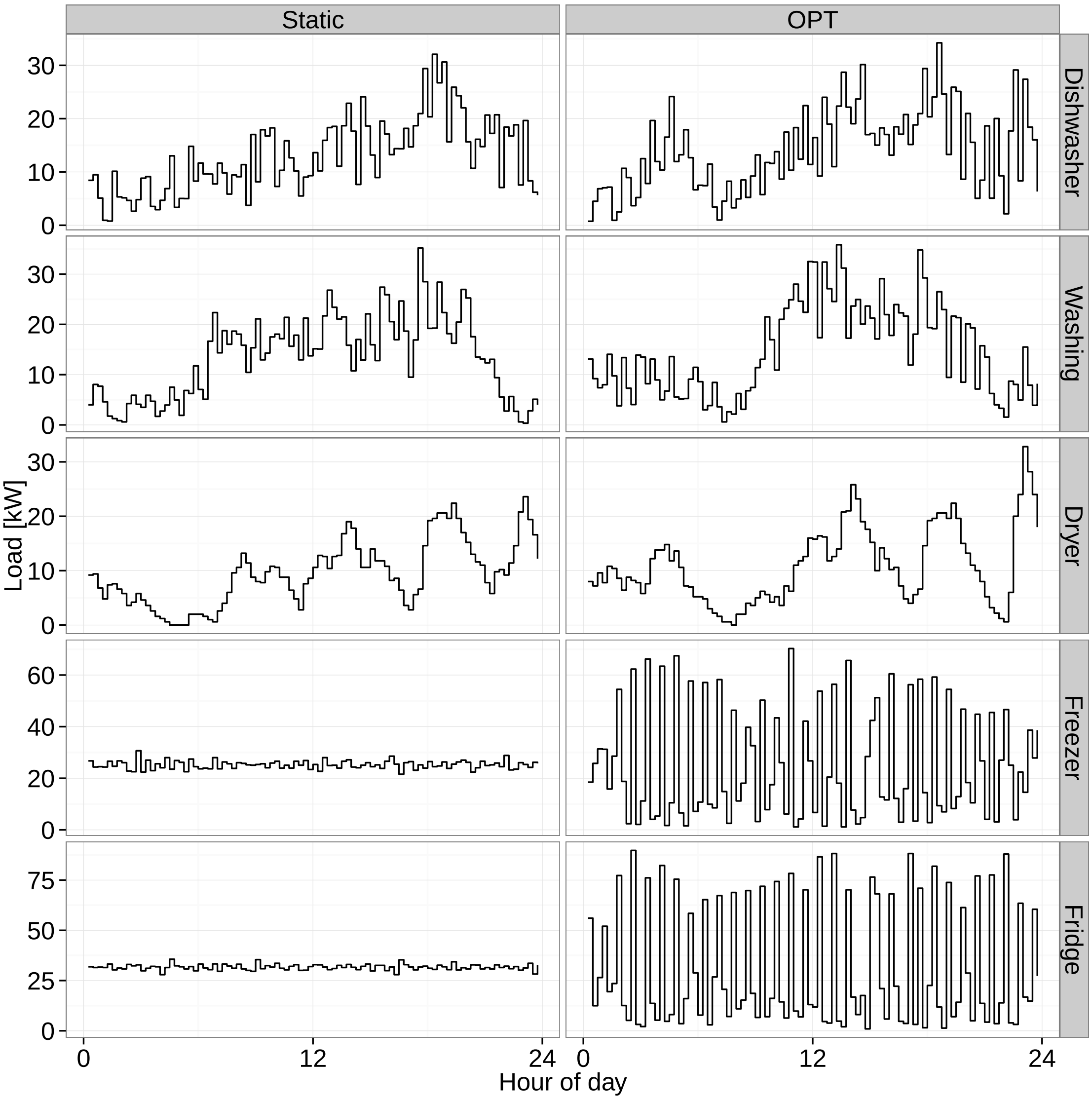

Figure D.2: Load for uncontrolled (Static) and controlled (OPT) devices over one day

Appendix E

EV and Stationary Battery Calibration

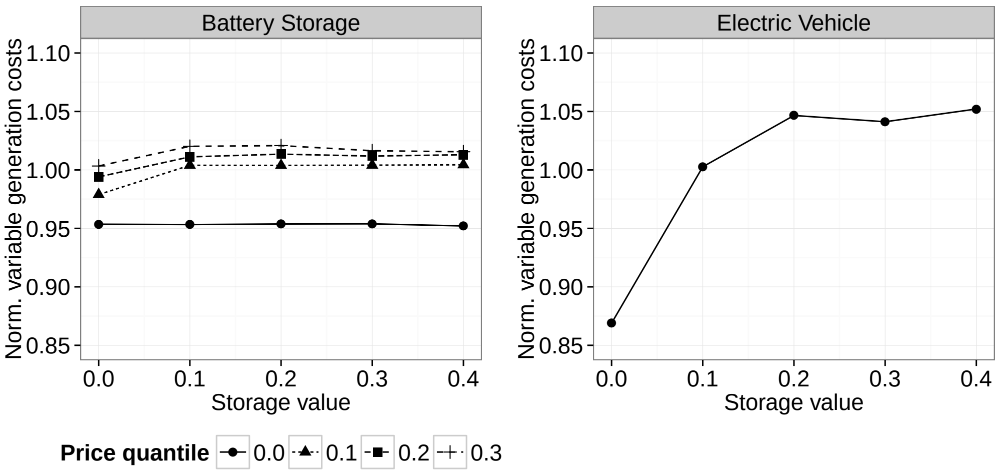

Figure E.1: Normalized variable generation costs for different storage values under RT pricing (for stationary batteries also price quantiles to govern charging ($\underline{p}$) and discharging (1-$\underline{p}$) activity are depicted)

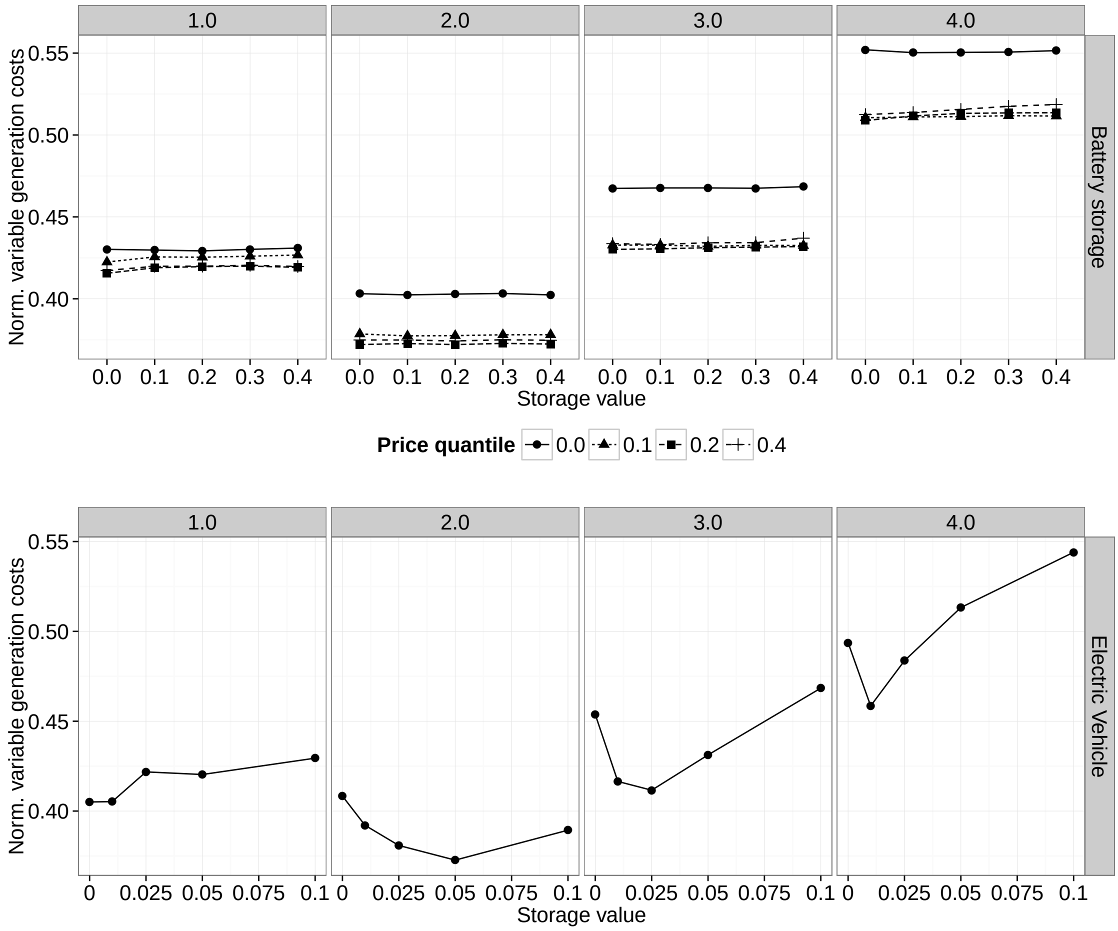

Figure E.2: Normalized variable generation costs for different randomization levels and storage values under group pricing (for stationary batteries also price quantiles to govern charging ($\underline{p}$) and discharging (1-$\underline{p}$) activity are depicted)