Flexible Demand in Smart Grids
Modeling and Coordination

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Dipl.-Wi.-Ing. Christoph Michael Flath

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Referent: Prof. Dr. Christof Weinhardt
Korreferent: Prof. Dr. Wolf Fichtner

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Abstract

The transition towards very high shares of fluctuating energy generation sources requires significant changes to the power system and electricity markets. Smart grids will play a key role in addressing this challenge. Through improved monitoring, forecasting and control capabilities they will be able to empower the so far passive demand side of the power system. Yet, the successful establishment of smart grids will require both sound technical *and* economic concepts. The economic analysis of smart grid capabilities needs to incorporate physical boundaries as hard constraints which need to be facilitated by means of flexibility potentials and intelligent dispatching. Due to the distributed nature of demand, economic coordination also needs to be able to facilitate a multitude of individual agents. Consequently, the design of future power systems and electricity markets needs to embrace the importance of distributed agents and facilitate their integration. The thesis follows this decentral and demand-centric vision of the smart grid. Questions concerning the modeling and coordination of an active demand side are addressed using tools and techniques from information systems and economics. Building on a framework for the design of smart grid customer models relevant coordination approaches are discussed. This framework is applied within two distinct application scenarios — household customer models and electric vehicle models.

Household customer models are derived by applying a cluster analysis to identify customer segments within smart metering data from a regional utilities company. This data mining approach reveals distinct customer segments which differ from standard load profiles. The customer heterogeneity motivates the design of customer-specific electricity rates. To this end, a mixed-integer optimization model to determine efficient time-of-use electricity rates for individual customer segments is proposed and evaluated. It obtains that rate update frequency is of greater importance than rate granularity.

Charging needs of electric vehicles are modeled using current technical specifications and empirical mobility data. Based on these model primitives, a variety of decision models encapsulating different price and trip information regimes are discussed and implemented. This allows assessing likely charging behavior of individual electric vehicles in the presence of different incentive schemes, battery wear or load-based demand charges. These individual models are then aggregated to analyze the load impact of population-wide charging behavior. Based on these population models, two charging load coordination mechanisms are discussed — locational pricing and capacity management. Using surcharges reflecting local transformer utilization, area pricing successfully mitigates violations of stability limits

while retaining the economic incentives of load shifting. The capacity management scheme can achieve similar coordination results using a non-price-based approach.

Describing novel modeling techniques and coordination approaches, this thesis contributes to the energy informatics literature and aims at establishing a notion of smart grid market design.

Acknowledgements

This work would not have been possible without the support of several people who contributed with ideas, conversations, guidance, and care. To begin, I am very thankful that my supervisor Prof. Dr. Christof Weinhardt gave me the opportunity to pursue my dissertation providing the necessary guidance while at the same time allowing me to freely develop my ideas. I would also like to thank co-advisor Prof. Dr. Wolf Fichtner, Prof. Dr. Thomas Setzer, and Prof. Dr. Orestis Terzidis, who have served on my thesis committee, for providing valuable comments and suggestions.

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Among the set of colleagues, it is my pleasure to express special thanks to a selected group of people who for various reasons have played a very important role on my path to finishing my dissertation: Florian Teschner for making me believe in salad and my research. Benoît Chevalier-Roignant for being an amazing Frenchman. Jens for being the most supportive co-worker one can wish for. Sebastian Gottwalt for inspiring discussions on ants, football and electric vehicles. Philipp Ströhle for having taught me to trust in obscure tools. John Khawam for being one of the nicest and most helpful persons in the world. Rico Knapper for being a great Berlin guide and "co-sufferer". Alex Schuller for his patient and calm nature. David Dauer for his never-ending programming resources. Timm Teubner for board games and football. Philipp Astor for the Cannoli.

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

Reduction of carbon emissions and increased independence from resource imports are central goals of the European Union. In 2010, the member states committed to a significant reduction of greenhouse gas emissions (20% over the 1990 levels by 2020). Furthermore, at least one fifth of energy consumption is to be covered from renewable sources. The Energy Roadmap 2050[1] significantly extends these goals and envisions a virtually carbon-free European power system by 2050:

> *"The EU goal to cut greenhouse gas emissions by 80–95% by 2050 has serious implications for our energy system. [...] Electricity production needs to be almost emission-free, despite higher demand."*

The necessary large-scale integration of renewable energy sources required to achieve these ambitious goals necessitates a transition from a traditional centralized power system based on conventional and controllable generators towards a system incorporating a multitude of distributed and intermittent generators (e.g., solar panels, micro-Combined Heat and Power (CHP) plants or wind turbines). The Energy Roadmap 2050 confirms this observation and notes, that

> *"our energy system has not [...] been designed to deal with such challenges. By 2050, it must be transformed. Only a new energy model will make our system secure, competitive and sustainable in the long-run."*

To achieve these goals, the "new energy model" needs new forms of electricity generation as well as a new control approach to ensure stable system operations: Historically, the balance of system load and generation — crucial for grid stability — was maintained through central control of storage systems and conventional power plants (Stoft, 2002). However, intermittent generators cannot offer this degree of supply flexibility and centralized electricity storage is very costly (Ahlert and Block, 2010). Therefore, new ways of grid balancing will be needed.

[1] Details concerning the 2020 goals and the Energy Roadmap can be found at `ec.europa.eu/europe2020/targets/eu-targets` and `ec.europa.eu/energy/energy2020/roadmap/index_en.htm`.

A promising approach is fostering Demand Response (DR), that is engaging the demand side to adapt its energy consumption through monetary incentives or direct load control (Albadi and El-Saadany, 2008). These approaches are likely to increase load flexibility which helps to compensate the inflexibility of intermittent generators. Implementing DR approaches requires upgrading electric distribution grids with Information and Communication Technology (ICT) equipment (Amin and Wollenberg, 2005; Block et al., 2008; Appelrath et al., 2012) to create a *smart grid*. Smart grids connect and control generators, storage devices and intelligent appliances by means of ICT (DKE, 2010). Establishing the smart grid will require significant infrastructure investments. Furthermore, it poses challenges to the electricity system along various dimensions: interoperability and technological standards, coordination and control structures, system security, as well as privacy and data protection.

1.1 Smart grids as Techno-Economic Systems

Research on smart grids so far focused on technological demonstration projects.[2] This research has provided valuable insights concerning technological feasibility (von Dollen, 2009) as well as possible adoption and implementation paths (Ipakchi and Albuyeh, 2009; Faruqui et al., 2009; Farhangi, 2010). However, the infrastructure is only one part of the smart grid system, the other being business models established on top of this technical system (Block et al., 2008). An important precursor for such smart grid market research was the Self Organization & Spontaneity in Liberalized and Harmonized Markets (SESAM) project, see e.g., Rolli et al. (2004) or Esser et al. (2007). SESAM for the first time identified economic design challenges in new energy markets and outlined novel solution approaches. Figure 1.1 illustrates a conceptual framework of the electricity system as a combination of technical equipment, ICT systems and business models. While the technological foundations are necessary for creating an intelligent energy system, it is the economic incentives that may ultimately decide whether and how potential stakeholders will participate in such a system.

The focus on aligned system coordination marks a shift in the smart grid research agenda — away from implementation tasks towards "engineering" a techno-economic system as a whole (Roth, 2002). The market engineering framework as proposed by Weinhardt et al. (2003) establishes a coherent system for designing electronic market platforms which help guiding design decision for ICT-based markets. Consequently, Weinhardt (2012) adopts this framework for smart grid markets.

[2] Some more recent exemplary projects include the the e-Energy model regions in Germany (`www.e-energy.de`), the Pacific Northwest Smart Grid Demonstration Project (`www.pnwsmartgrid.org`) or the Smart Energy Collective (`www.smartenergycollective.nl`).

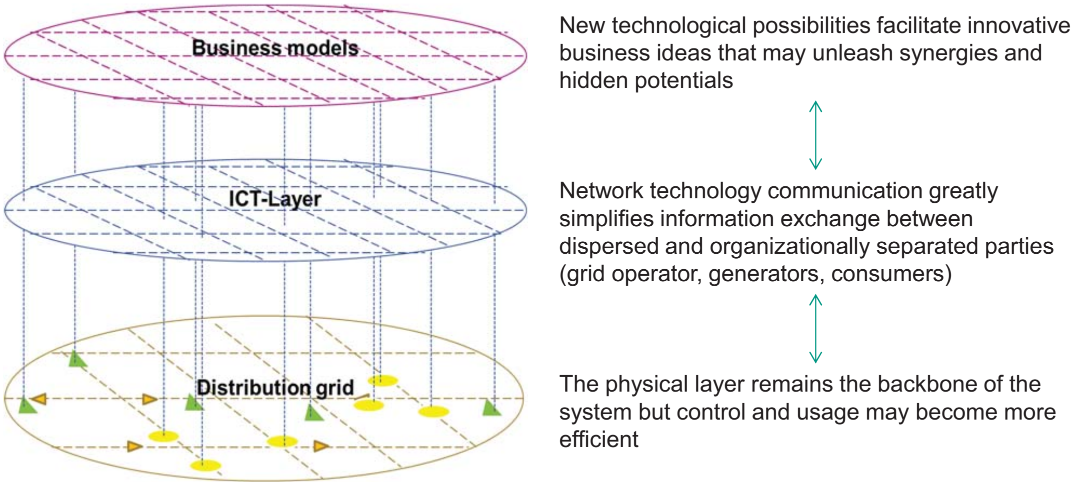


Figure 1.1: ICT connects physical and market layer in the smart grid (Block et al., 2008)

1.2 Smart Grid Economics

Given the efficiency potentials of novel incentive systems in the retail electricity market (e.g., Borenstein et al., 2002; Chassin and Kiesling, 2008), the economic analysis of smart grids is of great importance. Yet relevant insights on the economics of smart grid systems remain limited. Consequently, establishing the concept of Smart Grid Economics (SGE) as coined by Chapel (2008) will require a holistic system design taking into account both technical *and* economic constraints. It is illustrative to look at two characteristic problems in smart grid systems that may arise from an incomplete economic analysis:

Avalanche Effects Exogenously set price patterns — e.g., pre-specified Time-Of-Use (TOU) electricity rates — are likely to induce situations of over-coordination where a large number of customers jointly respond to a discrete lower price level (Ramchurn et al., 2012). This herding may yield significant load spikes defeating the original goal of price-based coordination, i.e. shaping the load profile to match current system conditions. Gottwalt et al. (2011) refer to this problem as the "avalanche-effect" of TOU electricity pricing. Interestingly, many current projects still envision such exogenous time-varying rates as the preferred coordination instrument.

Strategic Behavior Another pitfall of technically oriented research projects is ignoring the strategic nature of economic interactions: Engineers often design and evaluate complex systems implicitly assuming that system participants will truthfully disclose individual costs, availability or service level requirements. These reports are then used to determine efficient payments and resource allocations accordingly.[3] However, in many cases non-truthful reports may improve a participant's individual welfare. The literature on economic mechanism design (see Dasgupta et al., 1979; Nisan and Ronen, 2001; Dash

[3] Another point in case is retail supply chain management where the impact from strategic behavior of buyers has also been ignored for a long time (Su and Zhang, 2008).

et al., 2003) indicates that this is a problem of incentive-compatibility. Hence, efficiency potentials reported from non-strategic evaluation of smart grid systems may potentially be too optimistic.

Recognizing these obstacles, I am interested in economic mechanisms that can achieve the desired coordination of system participants while taking into account the emergent behavior within larger populations of self-interested actors. Only recently, research on the underlying economic interactions and incentives in smart grids have emerged: For example, Block et al. (2010) and Vytelingum et al. (2010) discuss trading agent approaches for smart grids, Ahlert and Block (2010), Ramchurn et al. (2011) and Gottwalt et al. (2011) discuss economic control of storage systems and smart homes, while Gerding et al. (2011) analyze online mechanism design for electric vehicle charging.

1.3 Research Questions & Problem Description

This thesis aims to model and evaluate future smart grids as economic systems. This follows the smart grid market engineering proposal due to Weinhardt (2012). Acknowledging the ideas put forward by Ostrom (2010), I do not exclusively focus on "markets" in the literal sense but instead consider decentral (polycentric) systems in general. Therefore, in the remainder the term market will, if not indicated otherwise, describe a microeconomic system as defined by Smith (1982) — an economic environment (population) and an economic institution (mechanism).[4] This motivates the overarching research question of this thesis:

Research Question 1 – SMART GRID MARKETS. *What characterizes a feasible modeling and evaluation approach for representing the market layer of the smart grid as a microeconomic system?*

Building on Smith (1982), Ostrom (2010) and Weinhardt (2012) I structure the research along the population (customers) and economic institutions (coordination mechanisms) as shown in Figure 1.2. I focus on these two core elements to better analyze the economic problems arising in polycentric smart grid markets. This requires developing appropriate modeling techniques to capture diverse smart grid populations which may feature, e.g., smart homes, Electric Vehicles (EVs), storage systems or heat pumps. As noted before, the demand side is of special interest in the future energy system. Therefore, I want to focus on developing and evaluating techniques for creating customer models. These need to represent the technological properties, information availability and customer usage behavior. Similarly, it is important to identify and evaluate appropriate coordination mechanisms to achieve fair, reliable and (economically and ecologically) efficient allocation of limited grid resources taking into account the regulatory regime. These two elements — cus-

[4] With respect to the market engineering framework, these elements correspond to the market participants and the market microstructure.

tomer models and coordination mechanisms — allow us to represent and correspondingly account for economic objectives when designing smart grid systems.

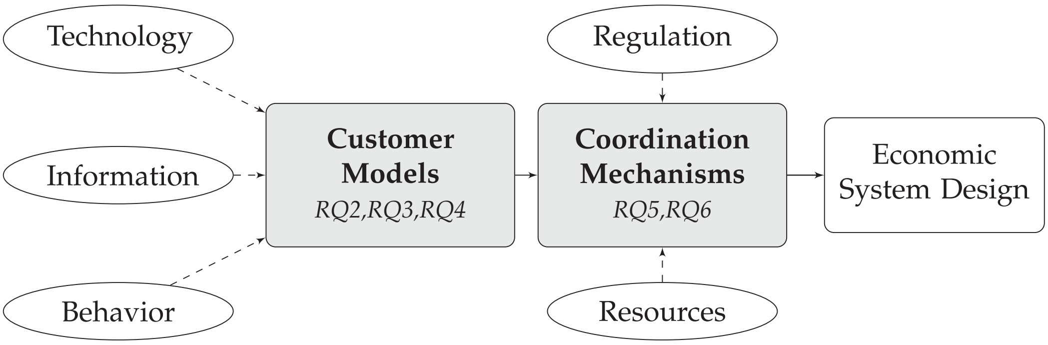


Figure 1.2: Research Model

1.3.1 Modeling Smart Grid Customers

Keshav and Rosenberg (2011), as well as Ramchurn et al. (2012) illustrate how smart grid design can leverage on concepts from the domains of internet communication and artificial intelligence. A key aspect in their observations is the decentral nature of the smart grid which is constituted by a multitude of individuals which each are *small* compared to the aggregate system. Thus, coordination of dispersed entities is a major task in smart grid systems. Following the notion of experimental and computational economics these individuals are interpreted as economic agents (Holland and Miller, 1991). Given appropriate agent models the emergent aggregate behavior of an agent population can be used to characterize likely system behavior. These tasks motivate the second research question:

Research Question 2 – GENERAL CUSTOMER MODELING. *What characterizes smart grid customer models?*

A key distinction for customer models is model scope — that is the modeling granularity chosen to represent the real-world entity. Top-down models provide a stylized means from a macro-perspective to model a larger group of similar customers. These models are especially relevant for representing aggregated populations. On the other hand, bottom-up modeling aims to establish micro-foundation of agent actions on an elementary level by representing individual customer properties in high detail. Given the generic customer model specification it is of special interest to apply it to concrete use cases. Modeling household customers serves as a natural starting point. To complement current bottom-up models (e.g., Gottwalt et al., 2011) a top-down modeling approaches with similar expressiveness is proposed. This approach leverages the availability of smart metering data which should be available from an increasing number of households in the future. In a similar fashion, EV fleets are also modeled in a top-down manner.

Research Question 3 – SMART GRID MODEL SCOPE. *Can top-down customer models be derived to represent household or EV population demand in a compact top-down manner?*

A novel electrical load of increasing importance are EVs which can be connected directly to the electrical grid for charging their batteries (Clement-Nyns et al., 2011; Galus et al., 2009). With increasing prevalence and shifting flexibility EVs may very well attain a central role in smart grid coordination constituting a significant load share in distribution grids. Consequently, EV charging activity needs to be carefully analyzed in order to build meaningful and robust smart grid models. I want to enhance current EV modeling approaches (Dietz et al., 2011; Lopes et al., 2009) by explicitly accounting for uncertainty with respect to electricity prices and mobility behavior.

Research Question 4 – ELECTRIC VEHICLE CUSTOMER MODELS. *What is the impact of price and trip uncertainty on electric vehicle charging behavior?*

Addressing these questions, allows modeling smart grid customers in a coherent and multi-faceted way. This facilitates proper design and evaluation of economic coordination mechanisms for the smart grid which ultimately will allow establishing a better smart grid.

1.3.2 Smart Grid Coordination

Having established appropriate smart grid modeling principles, coordination mechanism for allocating grid resources in an efficient manner can be designed and evaluated. Resources in the electricity system encompass generation, line and transformer capacities across space and time (cf. Bohn et al., 1984). To characterize the coordination goals the resources most relevant in the smart grid scenario need to be identified:

Research Question 5 – SMART GRID RESOURCES. *What are relevant resource bottlenecks and coordination goals in smart grid scenarios?*

Economic coordination mechanisms can be price-, capacity- or market-based and need to allocate the available resources while achieving good overall system efficiency (with respect to, e.g., profits, social welfare, costs or emissions). As noted before avalanche effects have been identified as a major drawback of exogenous price signals. Therefore, smart grid coordination needs to pay special attention to such over-coordination effects. This mandates both careful design and an appropriate evaluation, e.g., using simulation tools, to ensure the robustness of a coordination mechanism. Furthermore, I am interested in coordination approaches of limited to complexity to maintain both comprehensibility as well as transparency which are crucial success factors in real word application scenarios.

By explicitly accounting for the economic behavior of smart grid agents I want to identify appropriate economic coordination mechanisms:

Research Question 6 – Coordination Mechanisms. *Which coordination mechanisms are appropriate for different resources in the smart grid?*

1.4 Structure

This section provides a short outline of the thesis structure (see Figure 1.3). Chapter 2 introduces the fundamentals of power systems and smart grids. The following Chapter 3 lays out the *Customer Modeling* framework used in the remainder of the thesis. In addition to modeling, this thesis also focuses *Smart Grid Coordination* as described in Section 1.3. These two main branches are addressed for different customer types in two main parts: Within Part II household customer models are created using smart meter data (Chapter 4). In Chapter 5 a Mixed-Integer-Program (MIP) approach for customized rate design is developed and evaluated. Part III focuses on electric vehicle customers. In Chapter 6 different models for representing individual EVs are described and evaluated. Chapter 7 looks at vehicle population models and appropriate coordination approaches. Chapter 8 summarizes and evaluates the research contribution. Chapter 9 concludes and provides an outlook on subsequent research opportunities.

1.5 Research Path

As this thesis spans research activity over a time span of several years some of the research contributions were previously published in conference proceedings and journals. This section provides an overview and relates the contents of the thesis to these research activities.

- The customer modeling framework proposed in Chapter 3 is part of the Power TAC game specification (Ketter et al., 2011).
- The rate selection process as described in Chapter 3 was adopted for a conference paper on IT service portfolio design at the *IEEE International Conference on Service Oriented Computing & Applications 2011* (Knapper et al., 2011). A related model was used in an article on cloud service brokering which was published in the *International Journal of Computational Science and Engineering* (Jrad et al., 2013).
- The material on dynamic investment in Chapter 3 is a smart grid adopted version of a full paper on optimal investment decisions in the presence of strategic

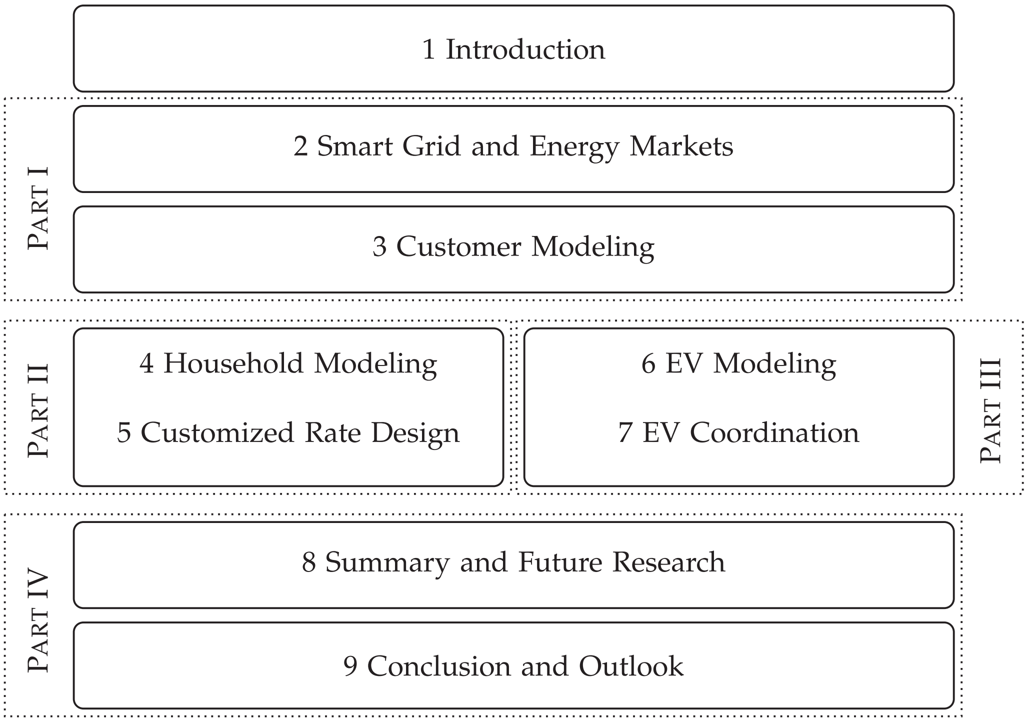


Figure 1.3: Structure of the Thesis

interactions and uncertainty published in the *European Journal of Operational Research* (Chevalier-Roignant et al., 2011).

- The material on the cluster analysis in Chapter 4 was previously published in the *Wirtschaftsinformatik* Special Issue on the "Internet of Energy" (Flath et al., 2012).

- A very preliminary model for segment-specific rate design problem discussed in Chapter 5 was presented at the *Multikonferenz Wirtschaftsinformatik 2012* (Ighli et al., 2012).

- The formal EV charging model and the material on EV charging strategies in Chapter 6 are extensions of papers presented at the *Americas Conference on Information Systems 2012* (Flath et al., 2012) and accepted for publication in *Transportation Science* (Flath et al., 2013). The latter also describes the locational pricing used in Chapter 7. An additional paper on a corresponding case study with a Swiss grid operator is currently under review with *Energy Policy* (Salah et al., 2011) (revise and resubmit).

- The capacity management approach described in Chapter 7 was previously published as a conference paper at the *Hawaii International Conference on System Sciences 2012* (Flath et al., 2012).

These sources are mentioned explicitly in the corresponding parts of this thesis.

Part I

Smart Grid Economics

Chapter 2

Smart Grid and Energy Markets

The electrical power system is crucial to the functioning of today's societies and economies. Established in the beginning of the last century this complex system has demonstrated great efficiency, scalability and reliability. This was achieved by means of a hierarchical approach using central and dispatchable large-scale power plants for generation and high voltage transmission lines for transport to serve low voltage distribution. The shift towards a major share of decentral and intermittent generation units poses a fundamental challenge to retain these historic stability and efficiency levels. The development of the smart grid is a crucial prerequisite to realize potential advantages through integration of flexible loads in the future power system.

This chapter provides a brief overview of traditional power system design aspects and identifies relevant coordination criteria within this setting. Subsequently, the characteristics and potentials of smart grids are discussed.

2.1 Electricity Value Chain

The value chain of today's power system is spanned by the fundamental functions generation, transmission, distribution and consumption. Figure 2.1 shows this value chain and emphasizes the fact that these generic functions encompass very heterogeneous sub-functions. Given the non-storability of electricity and the instantaneous nature of electrical currents, this value chain is highly integrated with individual functions being highly dependent on each other. The synergies from joint cental operations are one of the reasons why the supply functions (generation, transmission and distribution) were historically performed by large integrated utilities companies. However, following the regulatory unbundling requirements enacted within the liberalization of electricity markets generation activities were separated from grid operations (Joskow, 2008a). Generation companies are active in a competitive (wholesale) market, while grid operators are regulated monopolies. In the following, these different functions are discussed in detail.

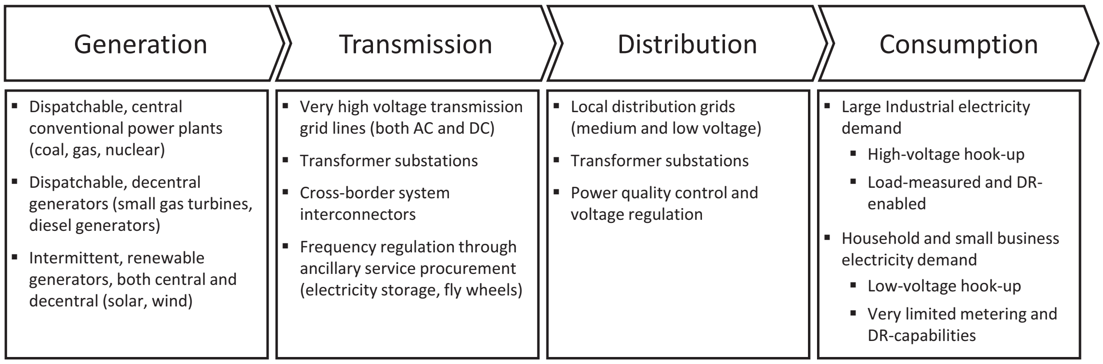


Figure 2.1: Functions and Sub-Functions in the Electricity Value Chain

2.1.1 Generation

As noted before, electricity generation options are fairly heterogeneous with significant differences with respect to inputs, operation and capacity costs, scale, location, reliability or flexibility. Figure 2.2 illustrates this diversity for the German market. All generation technologies feature relevant shares of installed capacity. In recent years, the installed capacity of renewable energy generation has grown significantly in recent years. At the same time, the effective net output illustrates the distinctly different plant utilization patterns. Lignite coal, nuclear power and to a lesser extent Anthracite coal plants are classic examples for base load plants that are operated in a continuous fashion with minimal ramping. On the other hand oil, natural gas and pumped hydro plants are used on a less constant base but rather are ramped frequently in response to current system and market conditions. Finally, intermittent, renewable energy sources (Photovoltaic (PV), wind) are operated in an always-on fashion but exhibit low availability levels due to their stochastic generation profile.

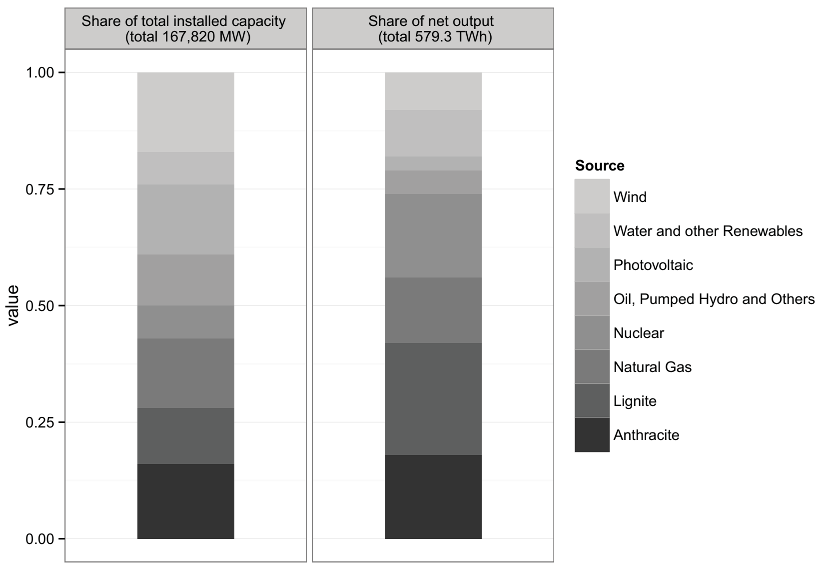


Figure 2.2: Capacity and output share of different energy sources in Germany 2011 (BDEW, 2012)

These utilization patterns are driven by the plants' fundamental operational properties — marginal cost of generation on the one hand, ramping costs, operational constraints and availability on the other. Given a portfolio of generators, generation units are typically dispatched in order of increasing marginal generation cost taking into account availability and ramping constraints (Stoft, 2002; Schweppe et al., 1988). This yields the so-called merit order dispatch as shown in Figure 2.3.[1] Besides the dispatch schedule, the merit order curve also indicates the market price at the intersection of the demand and supply curve. The supply from additional low marginal cost generators from renewable generation shifts the merit order curve to the right and thus reduces the market price. This is referred to as the merit order effect of renewable energies (Sensfuss et al., 2008). This effect becomes evident when comparing the left and right panel of Figure 2.3.

The stochastic nature of electricity demand requires a technological mix of base- and peak-load power plants. While operational costs and constraints are the central factor behind dispatch decisions, investment decision are additionally governed by capacity costs. Plant investors thus need to balance capacity investments and operational costs against market revenues from the wholesale electricity market to formulate investment decisions. Recently, however, this energy-focused remuneration has been challenged by falling wholesale prices due to generation from renewable energy sources which may no longer cover operational and capacity costs. This "missing money" problem[2] for conventional generation is amplified by the fact that renewable generators are typically subsidized in the form of feed-in tariffs or investment rebates to ensure investment viability (Haas et al., 2004). This has spurred discussions aiming for a more integrated market design honoring both capacity provision and energy supply through the creation of capacity markets (Cramton and Stoft, 2005; Creti and Fabra, 2007).

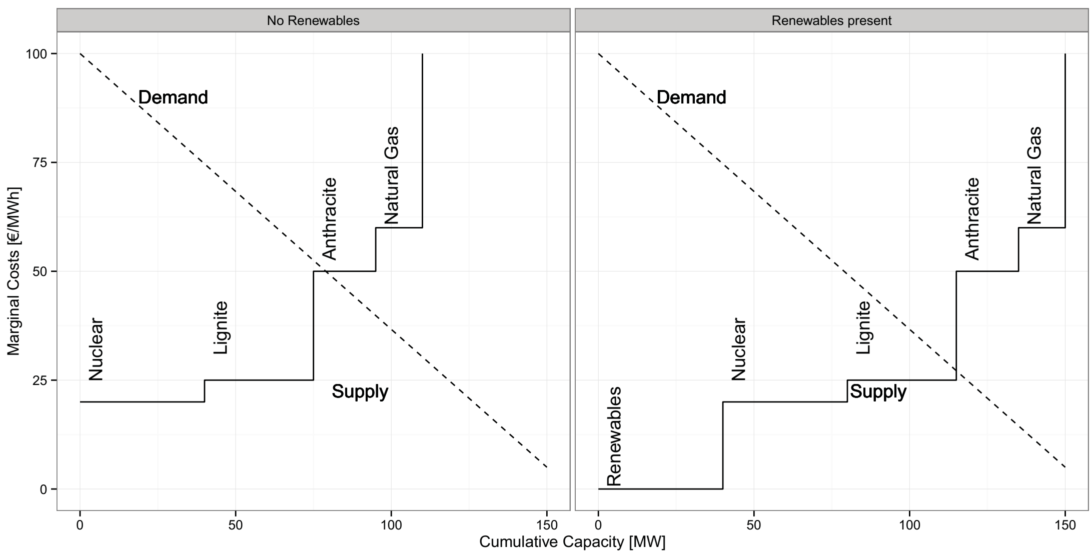


Figure 2.3: Merit order curve of electricity generation and the impact of renewable energy sources (Sensfuss et al., 2008)

[1] For an in-depth treatise of economic dispatch decision, see Schweppe et al. (1988, Appendix B).

[2] See Cramton and Stoft (2006), Joskow (2008b) or Mount et al. (2010) for a detailed treatise of the missing money discussion.

2.1.2 Transmission and Distribution

Power plant economies of scale, heterogeneous availability of natural resources and other locational factors as well as risk management aspects have been the major reasons behind the emergence of centralized electricity generation. This has spurred the development of high-voltage transmission grids for inter-regional electricity transport and medium-to-low-voltage distribution grids for customer supply. Germany has approximately 35,000 km of high voltage transmission lines operated at 220 and 380 kV (BDEW, 2012). Similar to other network industries, electricity grids are characterized by high investment costs and very low operational costs (maintenance, management and losses[3]). Therefore, they are considered as natural monopolies (Train, 2003) and subject to regulatory supervision as well as price regulation (Jamasb and Pollitt, 2000).

Transmission and distribution costs are typically allocated according to individual energy consumption for residential and small business customers whereas industrial customers often are power-metered and billed accordingly, e.g., using power-based load measurement (RLM). Demand charges are a variant to energy-only pricing observed in some markets. Here, customer grid costs are based on their maximum load level (Neufeld, 1987; Taylor and Schwarz, 1990) while consumption is billed based on energy consumption. This can facilitate a more transparent and fairer cost allocation but also requires more sophisticated metering equipment. Furthermore, Bohn (1982) notes that this billing approach will not necessarily maximize system efficiency.

2.1.3 Consumption

Naturally, the demand side of the power system is even more heterogeneous than the supply side. Table 2.1 provides an overview of the load shares of the different sectors of the German economy. These different sectors exhibit a wide range of total scale, temporal patterns as well as flexibility potentials with respect to their electricity demand. The latter is a central point. Demand in the current electricity system exhibits very limited responsiveness. This is both due to a lack of incentives (linear electricity rates) and technical limitations (simple metering equipment). Complex rates as well as sophisticated metering are costly and consequently it is mostly large industrial customers who are currently equipped with the relevant systems. The transition towards a smarter grid and decreasing system costs create the base for a more responsive demand. In combination with new incentive schemes, this will in the future facilitate participation of a larger share of customers through Demand Side Management (DSM). Then, both generation and demand can jointly and more efficiently contribute to system stability (Gonatas, 2012). It seems plausible that the heterogeneity of customer load profiles will facilitate the creation of custom DSM pools which will benefit from complementary demand properties. This is because customer heterogeneity allows to achieve more efficient allocations through appropriate trade-offs.

[3]In Germany, transmission and distribution losses account for 4-5% of total electricity output (`data.worldbank.org/indicator/EG.ELC.LOSS.ZS`).

Table 2.1: Net load of different industry sectors in Germany, 2011 (BDEW, 2012)

Sector	Net load
Industry	249.6 TWh (46.6%)
Households	136.6 TWh (25.5%)
Trade and Service	76.5 TWh (14.3%)
Public Service	46.9 TWh (8.8%)
Transportation	16.6 TWh (3.1%)
Agriculture	9.0 TWh (1.7%)
Total	535.2 TWh

Yet, the economic viability of DSM for household customers may currently be limited in the absence of automatic appliances Gottwalt et al. (2011) and electric vehicles (Flath et al., 2012). On the other hand, industrial customers already exhibit significant load flexibility potentials as demonstrated by the increasing presence of DSM aggregators such as EnerNOC in the USA or Entelios in Germany (Schisler et al., 2008). These services leverage untapped load flexibility embedded in customers' processes and systems. Going beyond committed flexibility resources, future emergency procedures should also account for the value of operations of certain customers. Table 2.2 illustrates the great differences in outage costs for different industries. Again heterogeneity would facilitate the identification and realization of more efficient allocation of available electricity resources, e.g., by inducing selective black-outs on customers in a lower service tier to shield higher service classes. Such reliability (service quality) tiering is considered a major opportunity in future smart grids (Varaiya et al., 2011; Stroehle et al., 2012).

Table 2.2: Average cost of a one hour interruption for different industries (Galvin Electricity Initiative, 2011)

Industry	Average cost of 1-Hour Interruption
Cellular communications	\$41,000
Telephone ticket sales	\$72,000
Airline reservation system	\$90,000
Semiconductor manufacturer	\$2,000,000
Credit card operation	\$2,580,000
Brokerage operation	\$6,480,000

2.1.4 Power Grid Structure

Besides the functional structure of the value chain, the modern power grid can also be structured along the voltage hierarchies. Transmission is more efficient at higher voltages while consumption occurs at medium to low voltage due to scale and safety reasons. This has spurred the development of the hierarchical structure of today's power grid as illustrated in Figure 2.4.

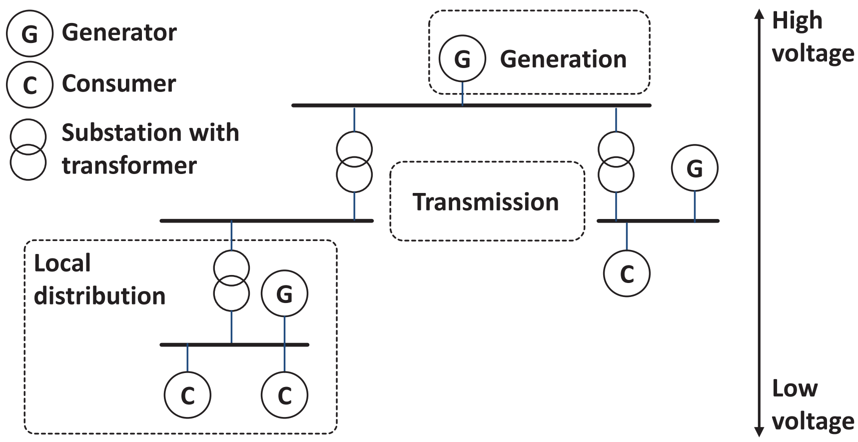


Figure 2.4: Basic structure and components of the electricity system

Generation typically takes place in a centralized fashion connected to the high-voltage grid while consumption typically occurs in the low voltage distribution grid. Exceptions are decentral generation occurring at lower voltage levels and industrial consumption occurring at higher voltage levels. Given the correspondence between the voltage level and the electricity functions, the power system is generally designed for uni-directional power flows from high to low voltage levels. However, growing amounts of renewable generation increase feed-in at lower voltages which may lead to more frequent power flow reversals (Turitsyn et al., 2010).

2.2 The Energy Trilemma

Efficiency of energy systems is typically assessed along the dimensions of costs (e.g., investment outlay, fuel usage, maintenance expenses), reliability (e.g., system availability, power quality) as well as ecological objectives (e.g., emissions, waste). These generic objectives are co-dependent and often inhibit one another: Lignite is a low cost and reliable energy source but creates very high emissions. Hence, economic trade-offs need to be made. Sautter et al. (2008) coined the term "energy trilemma" to refer to the trade-off between these conflicting objectives in the energy sector.[4]

To establish effective coordination in the power system, concrete coordination goals need to be identified in these categories to characterize appropriate trade-offs. Currently, reliability is typically treated as a hard constraint with system operators aiming for very high reliability levels at all times.[5] On the other hand, sustainability and costs are treated as competing objectives with support schemes fostering investments in (expensive) sustainable generation technology while market competition establishes incentives to reduce overall cost inefficiencies.

[4]In Germany, this trilemma is referred to as "Energewirtschaftliches Dreieck".
[5]Poudineh and Jamasb (2012) quote a target system reliability level of 99.97 percent.

2.2.1 Cost

As noted before, electricity system costs are two-part reflecting both marginal costs of electricity generation (e.g., fuel costs) as well as capacity costs of generators and the grid infrastructure. In the liberalized electricity market, generation costs result from wholesale market interaction while grid costs are regulated. Focusing on a stable set of generation and grid assets as well as assuming a competitive wholesale market, the minimization of procurement costs is the central objective for load-serving entities. By furthermore assuming a corresponding incentive structure and load flexibility individual customers' electricity demand would be aligned with this central price vector as well. The remainder of this thesis uses these assumptions as a base for evaluating economic coordination potentials. This is equivalent to a short-term operational perspective as opposed to long-term portfolio planning.

2.2.2 Reliability

Besides illustrating the structure of the power system, Figure 2.4 also facilitates the identification of three central operational capacity constraints:

1. Generation adequacy (Sufficient generation to serve load)
2. Transmission capacity (Intra-regional electricity transfer)
3. Capacity of local physical equipment (e.g., transformer capacity)

Depending on the scenario at hand, each of these bottlenecks may constitute a relevant coordination goal. However, this thesis focuses on the smart distribution grids and therefore the third constraint is of special interest. This is discussed for each capacity constraint in the following.

Generation adequacy

To guarantee stability and thus high system reliability in electrical grids, generation has to match consumption to ensure Alternating Current (AC) frequency stability.[6] If this crucial balance is not achieved, system stability is at risk and power quality is reduced, physical destruction of equipment or outages can occur. Currently, balancing is realized by a mixture of storage facilities, sophisticated forecasting tools and dispatching of large, centralized power plants increasing or decreasing their output. Ancillary service providers absorb deviations by providing short-term balancing for frequency stability (Stoft, 2002). The interaction of these components allows electricity generation to follow demand and balance the system.

Most theoretic models of power system coordination focus on addressing the generation adequacy constraint.[7] Instead of explicitly modeling system-wide sup-

[6] The rate of change of AC frequency is proportional to the mismatch between total generation G and total system load D, that is $\dot{f} \sim G - D$. Hence, frequency rises if generation is greater than the load and vice versa.

[7] Varaiya et al. (2011) also remark that "the simplest model of the power system is to ignore transmission constraints and focus only on adequacy of generation to meet load demand".

ply and demand balance it can typically be approximated through the procurement cost objective because of the direct correspondence between market price and the supply-demand-balance. Within this thesis, the latter approach is applied.

Transmission Capacity

Given the interconnectedness of the power system and the spatial separation of load and generation centers, the observation of transmission line capacities is a central in ensuring reliable system operations. Naturally, the direction and magnitude of power flows in the grid are governed by physical laws and the current load situations at the individual nodes. Thus, grid operators can only ensure stable system states by influencing generation and load levels. This crucial task is supported by comprehensive surveillance and monitoring systems as well as redundant system layout. In the remainder of this thesis the focus lies on distribution level coordination challenges. Hence, transmission capacity is typically not considered.

Capacity of Local Physical Equipment

While transmission constraints arise from power flow limitations *between* nodes in the transmission grids, local constraints manifest themselves *within* a local node in the grid. The underlying reasons can be local line limits, transformer substation capacity limitations or unwanted power flow reversals. Violations of these limits have a limited, mostly local impact (e.g., voltage band deviations, premature aging of equipment, local black-outs). Therefore, distribution grids exhibit lower redundancy levels and limited monitoring capabilities compared to transmission grids.

Historically, distribution grids have exhibited very high reliability despite this limited surveillance. This is because of a combination of both capacity over-investment (worst case design) and stable operational conditions. Increasing levels of intermittent generation (especially PV) in distribution grids have lead to higher local in-feed as well as increasing volatility in low-voltage grids. Increasing electrification will at the same time introduce new and large loads (e.g., electric vehicles or heat pumps) which will put further stress on the distribution system. Going forward, new coordination and control approaches will be needed to avoid even higher over-investment levels. This way, system operators can jointly pursue both cost and reliability goals.

2.2.3 Sustainability

The third dimension of the energy trilemma is sustainability. The power system conflicts with sustainability goals with respect to CO_2 emissions as well as land usage of generation sites and transmission lines.[8] When considering the strategic long-term perspective, power system sustainability is a question of a "green" power system footprint. This includes low-emission portfolios and reducing the impact of grid

[8]It should be noted that there are other sustainability conflicts, e.g., radiation, when assessing nuclear power.

infrastructure on the ecosystem. These goals can be pursued through investment support schemes for renewable energy generators and regulatory requirements for transmission grid planning.

On the other hand, ensuring sustainability in a short-term perspective is mostly about ensuring a sustainable generation mix. Emission-free generators, i.e. wind and solar power, are intermittent and hence cannot be dispatched. Therefore, CO_2 emissions can be minimized by scheduling flexible loads to times of high availability of renewable generation. Interestingly, the goal of increased utilization of renewable generation is also aligned with cost goals as renewable generators have no marginal cost of generation. Vytelingum et al. (2010) note that average carbon content is typically increasing in system load and hence peak load reduction would support both sustainability and generation adequacy goals. However, it may be conflicting with transmission and distribution constraints due to spatial dispersion of generation (e.g., wind turbines in northern Germany, high local feed-in) and load (e.g., factories in southern Germany, high local load). Within this thesis, I am primarily considered with optimal short-term operational decisions. Hence, long-term portfolio planning (capacity) decisions are not accounted for.

2.3 Smart Grids

The smart grid provides possibilities to monitor and control the system status on a granular local level in real time. This extends grid operators' monitoring and control capabilities already present in today's high and extra-high voltage grids, to the distribution grid where supervision was so far impossible (Varaiya et al., 2011). Hence, distribution grid control can evolve from a "blind" manual operation mode into a more sophisticated dynamic task in a complex granular system (Ipakchi and Albuyeh, 2009) which enables operators to improve overall efficiency. This is key to achieving a better balance of supply and demand over space and time.

In addition to better data quality and higher accuracy in control and monitoring tasks, the possibility to exchange data and share information enables the development of new control and influence models — for example new decentralized algorithms or variable rates. In particular the historic rule that supply follows demand gradually changes into a more system with both sides playing an active role. Therefore, smart grid capabilities can foster the establishment of new business models and market systems in the distribution grid where economic coordination was hardly present so far (Figure 2.5).

The remainder of this chapter serves to provide an overview over different key aspects in smart grids. Demand side management and dynamic pricing are discussed as major efficiency levers.

2.3.1 Demand Side Management

A flexible demand is controlled or influenced by DSM system which potentially leads to benefits in power system. Such demand side management helps to address the central challenge of integrating fluctuating renewable energy sources into the

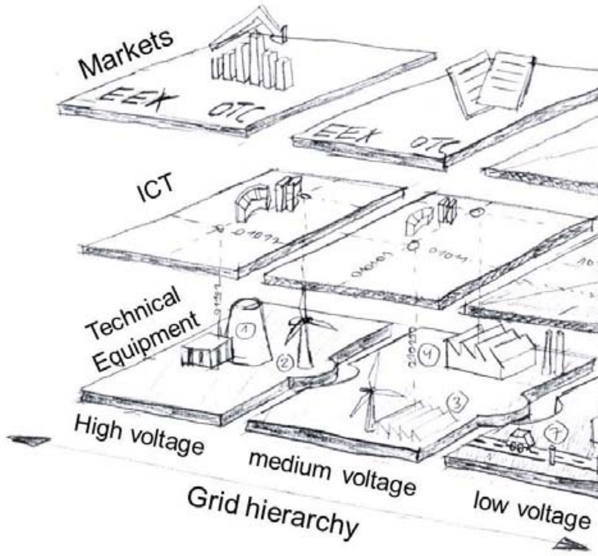


Figure 2.5: Layered model of the (future) energy system (BDI, 2011)

power system. DSM aims to adapt current *consumption* to current generation in order to maintain the balance between supply and demand.[9]

The visionary article by Schweppe et al. (1980) on homeostatic control proposed a consistent incentive system to reward system-compliant behavior of all power system participants. This work has subsequently been extended in (Schweppe et al., 1988). These abstract concepts were complemented with specific residential approaches in Schweppe et al. (1989). The authors provide a taxonomy of flexible devices distinguishing between thermal storage, periodic use devices, reschedulable and non-reschedulable appliances. Furthermore, the authors note, "[that] an end use device *uses* electric energy to provide a *service* to the customer." This differentiated view on electricity consumption paves the way for DSM approaches that adapt energy consumption to external signals such as availability of renewable generation, prices, system frequency or even temperature (Albadi and El-Saadany, 2008). Today, the most common DSM systems include night-time heating, direct-load control, time-of-use pricing, demand bidding and smart, i.e. price-responsive appliances. Going forward smart homes (Gottwalt et al., 2011) and electric vehicle charging (Flath et al., 2012) may emerge as a very flexible load types. Furthermore, researchers have proposed intelligent scheduling of CHP fleets (Bosman et al., 2012), prices-to-devices approaches (Sioshansi, 2011) or decentral optimization of integrated building energy systems (Hu et al., 2012). The challenges that DSM schemes have to overcome include, among others, inappropriate market structures and a lack of incentives (Strbac, 2008). Still, fostering DSM and demand side flexibility is an important element of cost-efficient smart grids as this may greatly decrease the costly storage investments.

Along with balancing generation and consumption, DSM can reduce investments in the grid and the cost of generation (Strbac, 2008) while customers can expect savings in their electricity bill (Albadi and El-Saadany, 2008). Two polar DSM

[9]Consumption flexibility is not only relevant in the context of smart grids and has also been investigated in more traditional areas, such as commuting (Small, 1982).

approaches are typically assumed: centralized direct load control and decentralized incentives to influence consumption. A mix of both approaches is decentralized load control based on local parameters and predefined contracts for specific loads. I will mainly focus on dynamic prices. Price-based coordination approaches are key concepts of DSM (Strbac, 2008).

2.3.2 Electricity Pricing

In their seminal work, Schweppe et al. (1988) provide an overview of the theory and implementation of time- and space-varying electricity prices. In addition to aggregate energy usage, individual user cost can dynamically depend on other attributes like usage, current load or aggregate consumption. However, in most countries residential electricity customers are still offered simple linear rates on total energy consumption. While utilities enter bilateral agreements with large industrial customers concerning sheddable load and peak prices, such contracts create inefficiently high transaction costs to be viable for residential and small business customers. In the latter case, dynamic pricing typically occurs in the form of simple TOU rates with two price levels — high prices in hours with high consumption and low prices typically during the night. Since these prices are not flexible in the short run, TOU rates are not flexible enough to influence consumer demand dynamically to achieve all benefits of DSM (Borenstein, 2005a).

Bohn et al. (1984) show that optimal spot pricing dynamically reflecting both system costs and constraints will lead to efficient allocations. However, this reasoning is based on a central planner perspective and is not necessarily robust to strategic considerations. Therefore, it is helpful to look at distinct value components for dynamic electricity pricing — time, location and load level:

Temporal Pricing The temporal component of electricity pricing should reflect the marginal cost of generation. In wholesale electricity markets, generators offer their electricity output to retailers. Marginal costs for the different power plants depend on fuel prices, operational costs and efficiency. Power plants are scheduled by using first generation units available with the lowest short-run marginal costs of production. Last in this order are typically peaking plants, e.g., gas turbines (Holmberg and Newbery, 2010). The last plant scheduled to cover electricity demand — the one with the highest marginal costs of all generators online — determines the power price for all generators in operation. Thus in times of high demand, generation costs are also high. Electricity prices in the wholesale market also reflect the generation of renewable sources. As wind turbines and solar power have almost zero marginal cost of generation and they displace peaking plants with high marginal costs. Therefore, in times of production from renewable sources the wholesale price is reduced (Sensfuss et al., 2008).

Spatial Pricing Cost of transmission and utilization of low-voltage grids are the fundamental drivers behind spatial price differences. Considering all operational constraints leads to individual nodal prices at each point where electricity is generated or consumed. However, such a system may be too complex for application on the end-customer level.

Zonal pricing reduces this complexity: Here, instead of pricing at each node groups of nodes are aggregated to larger zones. Within these zones prices are determined according to the system state. These zones can be pre-defined or dynamically established depending on grid conditions. Aggregating several nodes to larger zones reduces the pricing complexity and thus simplifies the application in practice. However, it also results in a loss of control granularity. Still, zonal pricing allows a reasonable trade-off between pricing complexity and the coordination ability of the pricing scheme (Leuthold et al., 2008).

Demand Charges Demand charges are a variant to energy-only pricing observed in some markets. Here, customer grid costs are based on their maximum load level (Neufeld, 1987; Taylor and Schwarz, 1990) while consumption is billed based on energy consumption. This can facilitate a more transparent and fairer cost allocation but also requires more sophisticated metering equipment. Furthermore, Bohn (1982) notes that this billing approach will not necessarily maximize system efficiency.

2.4 Discussion

The transition towards largely intermittent generation portfolios presents a disruptive change of today's power system. This change is guided by conflicting design objectives concerning system costs, reliability and sustainability. The smartening of the grid through Advanced Metering Infrastructure (AMI) and distributed control technology will play a crucial role in ensuring a viable power system. These changes create new challenges and opportunities for generators, grid operators and consumers. New incentive structures capable of conveying this market uncertainty will emerge. This development will help establish new business models. Information systems and economic coordination of the demand side will play a central role in this change.

In their recent review, Ramchurn et al. (2012) stressed the importance of distributed coordination and artificial intelligence approaches in the smart grid. They raised challenges to be tackled in the areas of DSM, EV charging control, virtual power plants, prosumers and self-healing networks. The design of the future power system and electricity market needs to embrace the importance of distributed agents and facilitate their integration. In the same vein, this thesis follows a demand-centric vision of a decentral smart grid.

Chapter 3

Customer Model Framework

Designers of future electricity markets are confronted with a large variety of actors and technologies. Thus, the analysis of these markets may easily become too complex for traditional planning and optimization approaches. Simulation-based approaches are a promising alternative; agent-based simulation models are particularly attractive since they facilitate a coherent and principled micro-foundation for the simulation environment (Bonabeau, 2002). The precondition of meaningful smart grid market simulation models is the implementation of robust and realistic customer models. For example, a standard household model should exhibit load behavior reflecting typical human activities (e.g., sleeping, working, getting sick, enjoying leisure activities, leaving on vacation) as well as a the technical equipment properties. Smart grid customer models also need to interact logically with diverse elements of a smart grid simulation environment such as time or weather conditions. Furthermore, in order to analyze economic coordination, customer models need to internalize incentives and respond accordingly with their decisions. Given the central theme of economic coordination these decision-theoretic modeling aspects are the the focus of this chapter.[1]

To structure the modeling process I use four levels (see Figure 3.1): The first level captures the static properties of a customer model and thus essentially describes its typical load patterns. To achieve a scalable smart grid model appropriate model size and scope to be determined. The choices here will crucially influence the third level — demand response characteristics. Here, the dynamic load behavior of a customer is characterized with respect to outside incentives. The relevance of the fourth modeling aspect, dynamic adaptivity, depends on the analysis goal. For analyzing short-term system behavior this level of detail is not required. However, when interested in dynamic evolution, e.g., migration paths and adoption behavior, one needs to model whether or not and how customers change tariffs and adopt new technical equipment. While I address all modeling levels in this chapter the main focus in the remainder of this thesis will lie on the second and third level.

[1]The customer modeling framework proposed in this chapter is part of the Power TAC game specification (Ketter et al., 2011).

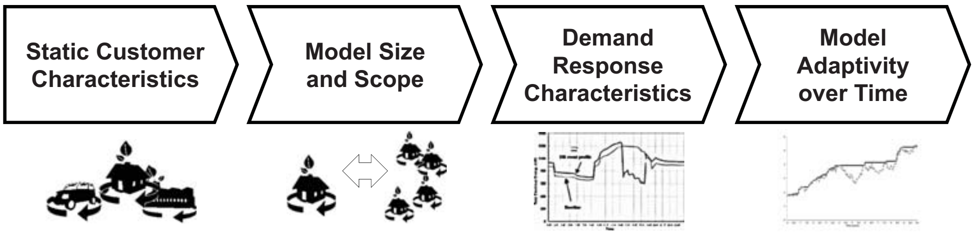


Figure 3.1: Four levels of customer modeling

3.1 Static Customer Characteristics

The most fundamental property of customer models are static customer characteristics which remain invariant over time. In the context of smart grid customer models, i.e. consumer of electricity, one is primarily interested in characteristics determining customer load behavior. These include technical specifications (e.g., maximum power level) as well as static usage patterns arising from inflexible consumption (milking machines on a farm). Reflecting these basic load patterns is a necessary first step for obtaining meaningful customer models. Yet, subsequent modeling steps are of similar importance.

3.2 Model Size and Scope

Creating customer models as true to life as possible improves the dynamics of the environment and may increase the plausibility of testbed scenarios (Hirsch et al., 2010). Only then can the resulting consumption and production patterns be considered valid. As crucial as this aspect is, it certainly has drawbacks. Smart grid market environments are characterized by a multitude of small actors. Establishing an increased degree of detail and decision-making freedom at the micro-level naturally gives rise to significant computational complexity which must be addressed. To guarantee scalable performance as well as a diverse simulation environment, efficient aggregation schemes are required. To this end, I want to look at the suitability of traditional Top-down and Bottom-Up models (Swan and Ugursal, 2009).

3.2.1 Top-Down Models

Top-down customer models typically represent entire system loads or customer segments (e.g., the German H0 load profile for households). These large groups are modeled in a synthetic manner based on historical load data records. For planning and load forecasting purposes these models are augmented with current weather conditions, calendar date information or economic indicators. Traditionally, this demand modeling approach has successfully allowed to maintain short-term system stability and has provided guidance for long-term planning of grid resources. Given their proven robustness, scalability and their simple input information (cf. Swan and Ugursal, 2009) top-down models will certainly play an important role for smart grid system analysis. Going forward, it is of special interest to obtain models for very specific customer types and reflecting some demand response capabilities (see Section 3.3). This is in line with Varaiya et al. (2011) who put forward the need for an approach that aggregates DSM capabilities of individual customers in a similar way as an availability curve of a renewable generator.

However, the aggregated nature of top-down models does not allow a detailed analysis of individual customer behavior. Therefore, they are less applicable for describing smaller scenarios where individual actions have a larger impact, e.g., microgrids (Block et al., 2008) or local energy cooperatives (Chalkiadakis et al., 2011). Furthermore, their reliance on historical data complicates their usage for modeling novel load types in future electricity systems. These limitations may necessitate the development of more expressive bottom-up models.

3.2.2 Bottom-up Models

Whereas top-down customer models generate load profiles from historic aggregate load data; bottom-up models determine the load from individual devices and consumption activities. These atomic usage decisions need to be explicitly scheduled given corresponding customer decisions. This approach facilitates the creation of rich customer models reflecting new load types and being able to engage in fairly complex demand response schemes. Yet with this level of detail come two distinct disadvantages over top-down models (Swan and Ugursal, 2009): The computational complexity of individual bottom-up models is exponential in the number of load types considered (Paatero and Lund, 2006). Thus, for real-time evaluation of larger populations this modeling technique may become infeasible. Furthermore, high levels of model detail will require significant amounts of input data to avoid arbitrary modeling assumptions. However, with comprehensive load measurements from future metering systems such data should be more readily available (Dalen and Weinhardt, 2012).

Summarizing, the bottom-up technique seems to be especially relevant for modeling customer models that exhibit high levels of flexibility (e.g., EVs or smart homes). In these cases the action space as well as the relevant incentive schemes may be fairly complex and thus warrant a detailed analysis. Isolating specific load types may facilitate hybrid approaches where highly flexible loads are modeled bottom-up and other load types are modeled top-down.

3.3 Load Response

While static load characteristics and model scope are key decisions when creating arbitrary customer models, it is the representation of load response capabilities that essentially creates "smart" customer behavior. Electricity consumption and production by retail customers depends on different factors, which can be grouped into three basic categories — *static*, *demand-response* and *environment-dependent* factors. Static factors are model primitives like household size, work shift hours or technical equipment, characterizing a customer's fundamental load profile. Demand response factors influencing the realization of customer load profiles describe the effect of different rate specifications, e.g., TOU, Real-Time Pricing (RTP) or interruptible load agreements. Lastly, environment-dependent factors represent load adjustments triggered by effects such as weather conditions.

Careful representation of static and weather-dependent factors is very important for building good models. However, this task essentially boils down to extensive analysis of empirical data to achieve the relevant statistical representation. On the other hand incorporating demand-response behavior requires appropriate decision-theoretic modeling to reflect the underlying economic behavior. Therefore, I provide an overview how to address this modeling challenge.

3.3.1 Demand Response

To properly capture the demand response paradigm, modeling the effect of electricity rates on customers' realized load patterns is of central interest for the economic analysis of smart grid systems. Customers' demand response potential (consumption and production flexibility) can be categorized along the dimensions of consumption amount and timing (see Figure 3.2). This way fully static models (I), models with static amounts and flexible timing (II), models with flexible amounts and static timing (III) as well as fully flexible models (IV) can be identified.

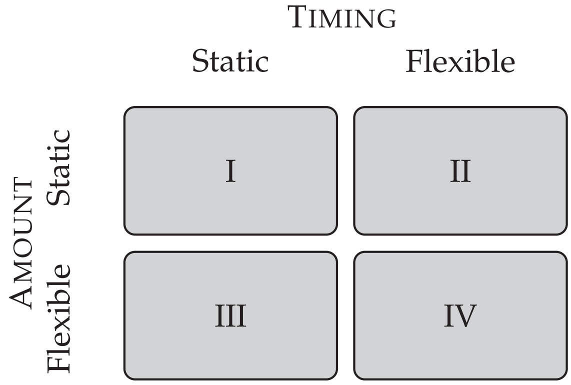


Figure 3.2: Characterization of demand response types

- **Fully static consumption** These are customer models that do not adjust their consumption to the rates of their current rate. This could be due to lack of shifting capabilities or relative insignificance of electricity costs or complete absence of flexibility incentives. This is also the appropriate model for non-controllable generation facilities (e.g., solar or wind).

- **Static amount, flexible timing of consumption** These customer models can change the timing of their loads (e.g., modify appliance scheduling) but cannot adjust the consumption amount. Under a given rate such models can minimize the cost of electricity by appropriately scheduling activities taking into account the relevant flexibility constraints.

- **Flexible amount, static timing** This type of customer model implements a simple demand behavior: at any point in time the optimal consumption amount is decreasing in the current electricity price. The typical case in point for this behavior is substitution: e.g., at low electricity prices a Plug-in Hybrid Electric vehicle (PHEV) could be run on electricity while at higher prices it may pay off to switch to gasoline (Gerding et al., 2011). Controllable generation units with well-defined cost functions (e.g., CHP units) are also captured by this modeling approach.

- **Fully dynamic consumption** Models with fully dynamic consumption feature both flexible consumption amounts as well as flexible consumption timing. Thus, fully dynamic models can endogenize price for activity occurrence and scheduling.

Clearly, type I is of limited interest when trying to model smart grid customers where the analysis of demand responsiveness is of central interest. At the same time static models are a natural starting point when considering the current state of customer flexibility. Moving to model types with demand response capabilities then requires integrating appropriate shifting and/ or adjustment capabilities in the static customer model.

3.3.2 Interruptible Capacity

Besides load shifting (also referred to as peak shaving or valley filling) another demand response paradigm is of special interest, interruptible capacity agreements and consumption-interruption programs. Such programs are described by Tuan and Bhattacharya (2003) and may offer significant additional benefits to improve grid stability. Under these schemes, customers transfer partial control of specific loads (e.g., EV charging, heat pump operations) to system operators, typically in exchange for some monetary compensation. Operators can use these control capabilities for load balancing by aggregating a large number of such customers.

Assessing the potential benefit of such interruption programs requires careful modeling of their effect on customer behavior: A simple approach is capturing these capabilities leveraging load-response capabilities as noted in 3.3. Then, charging a dynamic price $p \to \infty$ corresponds to requesting consumption interruption. However, this naïve will only work if customers' consumption flexibility is always sufficient to be able to avoid the usage charge of ∞ — that is, they need to either be able to shift consumption to a time with finite usage charge (type-II model) or reduce consumption to 0 (type-III). Otherwise, they would incur an ill-defined infinite charge which would render entering this load interruption agreement not acceptable for a customer in the first place.

A more coherent view on controllable loads is achieved when considering full availability vs. interruptible electricity service as quality-of-service classification for electricity provision. For a theoretical assessment of two-class electricity service I refer to Strauss and Oren (1993) as well as Chao et al. (1986).[2] Adopting this service quality view on interruptible electricity supply, appropriate customer models

[2]A somewhat related service discrimination concept are costly priority lanes in road transportation (Brownstone and Small, 2005). Customers also pay to obtain better service quality — similarly, interruptible load agreements specify savings in exchange for lower reliability.

need to implement distinct (but likely correlated) consumption behavior for these different service classes (e.g., electric heating would be interruptible, whereas stove usage would not). Within this framing the adoption of load interruption programs is consistent with customer utility maximization as they would cease consumption under interruption conditions. A key question is then the assessment of possible adoption patterns.

3.4 Model Adaptivity over Time

The previous modeling aspects addressed the representation of customers with static properties. Besides this static representation, endogenous changes to customers' load response behavior over time in response to market conditions are of special interest. From an economic point of view, dynamic acquisition of capabilities should fundamentally be driven by agents' individual benefits from these adoption choices. Heffner (2010) suggests different types of benefits from demand response and provides appropriate measures for estimation as well as corresponding analytic methods (see Table B.1). From this set I focus on the monetary evaluation criterion.[3] As described in Section 3.3 rate properties influence consumption behavior. Similarly, investment in new technical capabilities — e.g., storage or smart appliances — will also modify customer load behavior. Besides learning effects (Ramchurn et al., 2012; Dauer et al., 2013), committing to a new electricity rate or the acquisition of certain technical equipment are the main factors that dynamically influence changes in demand response behavior. To analyze a smart grid system's evolution it is necessary to capture these adoption dynamics. This allows identification of likely migration paths and estimation of equilibrium penetration levels. Such an assessment can help regulators guide market developments in the desired direction. In the following economic modeling of both capability adoption aspects are addressed.

3.4.1 Rate Utility and Selection

Smart grids may greatly reduce transaction costs in the retail energy market. This may establish new market roles and business models. Therefore, it is argued that competition may intensify (Vytelingum et al., 2010). There will be novel contract options and rate specifications from different suppliers from which customers will choose in a competitive market environment according to their needs and preferences. Consequently, the complexity of provider-customer relationships will increase. Regulatory guidance may be needed to achieve a fair and efficient rate market: For example, Borenstein et al. (2002) note the implicit adverse selection and fairness problems that may arise from voluntary RTP programs. Similarly, to protect customers from the in-transparency arising from a multitude of electricity rates the German Energy Industry Act (EnWG) emphasizes customer rights: The time for completing an electricity supplier change is limited and suppliers are required

[3]As always, alternative optimization goals (emissions, reliability) can be applied as well.

to provide their customers with concise billing documentation.[4] To address these problems arising from complex rate markets customer modeling needs to reflect the dynamics of rate switching processes.

A key element of modeling customer rate choice is determining an appropriate evaluation of rate attractiveness. Goett et al. (2000) and Gerpott and Paukert (2013) perform conjoint analyses to determine empirical distributions of customer preferences over different rate characteristics. Based on these results one can determine utility values for different rate specifications and subsequently characterize likely customer choice behavior. Roop and Fathelrahman (2003) wrap this approach in an agent-based simulation to determine customer choice between static, TOU and RTP rates. In the following a simple rate evaluation framework is sketched. This approach accounts for additional choice aspects compared to the one described by Roop and Fathelrahman.

In general, rate evaluation needs to account for expected cost as a major building block. This quantity obtains as the expected variable payments for electricity consumption.[5] The derivation of expected costs needs to properly reflect a customer's endogenous consumption choice under the rate to be evaluated. Therefore, rate choice needs to be anticipate and account for the potentially modified consumption plan under the new rate as described in Section 3.3. The monetary evaluation is complemented by an additional assessment of other rate aspects, e.g., energy sources or interruptibility properties. The rate utility function and the corresponding rate choice logic are the factors determining customer actions in a tariff market.

To illustrate a simple customer rate utility function I consider generalized additive independence between the attributes. Rate utility of a given rate i can then be represented as

$$u_i = -c_i \alpha_{cost} - r_i \alpha_{risk} - I_i \alpha_{inertia}, \tag{3.1}$$

where the alphas are customer-specific weighting parameters for the different rate-specific realizations of the sub-disutility types. The sub-disutility values for expected costs c_i, rate risk r_i, and customer inertia I_i can then be specified individually:

Expected Costs c_i Future consumption payments need to be estimated factoring in the endogenous consumption plan choice corresponding to the new rate. One approach is to sample k random days, deriving each day's consumption under the rate to be evaluated and finally averaging the realized costs $c_v^*(k)$:

$$c_v = \frac{\sum_k c_v^*(k)}{k}$$

For representative sampling over potential consumption and rate states this approach asymptotically yields an unbiased estimate of the expected rate costs.

[4] In particular, suppliers are required to explain the relevant calculation factors as well as the various price components and provide customers with a graphical depiction of their consumption profile.

[5] I abstract from fixed payments which are easily reflected by a corresponding offset value.

Rate Risk r_i Under a fully dynamic RTP rate customers face the risk of unfavorable rate developments. Following Borenstein et al. (2002) retail electricity customers should be assumed risk-averse and will thus have a preference for "bill stability". This indicates a negative utility from cost fluctuations. This is very similar to the expected return expected from risky financial investments: In the seminal portfolio selection model due to Markowitz (1952), the volatility of a risky asset must be compensated for by a higher expected return. Analogously, a dynamic rate's rate risk should be compensated by a lower expected total payment. Therefore, rate risk can be expressed as a function of the variance of expected payments. This variance can be approximated in the the same fashion as expected rate costs.

Customer Inertia I_i Faruqui et al. (2010) remark that customers may have behavioral costs of changing to a new rate. Such switching costs can be easily reflected by means of an inertia model as discussed by Train (2000). In its simplest formulation inertia I_i of a given rate i and the customer's current rate j is given by

$$I_i = \begin{cases} 1 & \text{if } i \neq j \\ 0 & \text{if } i = j. \end{cases} \tag{3.2}$$

Using varying levels of inertia costs $\alpha_{inertia}$ such models help explain why markets may only slowly converge to efficient adoption levels of variable tariffs.

Rate Choice A rate utility function specification like the one above allows assessing the utility of any rate offered. Based on a set of evaluated tariffs a customer model can choose the appropriate rate. An overall rate choice does not necessarily need to follow a deterministic choice of the highest utility value. A smoother decision rule which allocates the selection choice proportionally over multiple similar tariffs may be more appropriate. A logit choice model facilitates this type of rate choice randomization (Train, 2000). Instead of providing a discrete rate decision, a choice probability $\mathbb{P}_i$ is obtained for each rate i from the set of rate considered $\mathbb{T}$:

$$\mathbb{P}_i = \frac{e^{\lambda u_i}}{\sum_{t \in \mathbb{T}} e^{\lambda u_t}} \tag{3.3}$$

Here, the parameter $\lambda \geq 0$ is a measure for how rationally a customer chooses tariffs: $\lambda = 0$ represents random, irrational choice, while for $\lambda \to \infty$ the choice logic converges towards perfectly rational customers always choosing the highest utility value. Depending on the customer model type this choice probability can be used in two ways — either to represent somewhat randomized, not perfectly rational rate choice in case of single customer models or to assign population shares to different tariffs in case of a population customer model.

As mentioned before, variable rates between retail customers and distribution companies are central for establishing economic incentives in the smart grid. In order to achieve efficient matching of electricity consumer needs and generator capabilities contract relationships will become more heterogeneous. However, going forward customer-specific rate specifications tailored towards individual load properties can be imagined. These can further improve the matching of supply and demand. For example, such agreements may be necessary to facilitate complex customer relationships within virtual power plants (Ramchurn et al., 2012). Realizing such individual rate specifications will require some form of bilateral negotiations between providers and customers. Consequently, complex rate negotiations may constitute another step in improving coordination capabilities of Smart Grids.

3.4.2 Dynamic Investment Behavior

In a recent study[6] Steria Mummert, a consultancy, polled German local utility companies concerning their business plans to 2014. They found that less than half of the companies wanted to pursue smart grid investments. From a financial decision-making point of view this stance makes intuitive sense: The central obstacle in this context are the high investment outlays required in the presence of a highly stochastic market due to variable electricity prices as well as regulatory and technological changes. Several research contributions provide valuation models for smart grid investments (e.g., Sezgen et al., 2007; Ahlert and van Dinther, 2009; Dietz et al., 2011) yet these are typically formulated in a static setting and taking an individual customer's perspective. As such, these investment valuation models do not provide insights on possible migration paths. This gap is addressed by Vytelingum et al. (2010) who use agent-based modeling and evolutionary game theory to analyze population-wide storage adoption: They first determine the population-wide optimal aggregate storage level and then demonstrate that the equilibrium dynamically converges towards this level.

A similar adoption analysis can also be achieved with a more generic approach inspired by the literature on investment under uncertainty and competition (Chevalier-Roignant, Flath, Huchzermeier, and Trigeorgis, 2011). The remainder of this section serves to map smart grid adoption decisions to the framework proposed by Chevalier-Roignant et al.. For this I first reiterate the value of flexibility and optimal timing and then address the strategic interaction arising in competitive investment situations.

Value of Flexibility Investments in smart grid components extract a major part of their value from dynamic adjustments to current market situations.[7] The corresponding investment problem is thus not appropriately captured by a cash flow calculation based on static behavior but rather needs to take into account the optimal utilization of this flexibility.[8]

In the presence of a real-time price for electricity the market price can be applied as a natural underlying for the value of load adjustment capabilities. Sezgen et al. (2007) develop option valuation for determining the value of different demand response approaches focusing on load curtailment and load shifting. Assuming elec-

[6]`www.steria.com/de/presse/publikationen/studien/studien-details/?s_uid=168&cque=20`

[7]Clearly, the availability of variable rates is a prerequisite for the economic viability of costly demand response adoption (Ahlert and van Dinther, 2009).

[8]This is the analogue to the discussion on rate choice which also needs to factor in subsequent changes in load behavior.

tricity prices follow a geometric Brownian motion the value of these option values can be expressed using the Black-Scholes-Merton (Black and Scholes, 1973) option pricing approach. These stylized assumptions yield closed-form expressions for the investment values. Moving to numerical valuation methods (see Möst and Keles, 2010; Keles et al., 2012, for EEX price models) these methods can be adapted to richer and more realistic settings.

Optimal Investment Timing Valuation of a given investment opportunity is an important task. However, to assess the dynamic adoption behavior one needs not only to consider a momentary value but also needs to additionally identify the optimal timing of investment decisions. Using the analogy with an American call options McDonald and Siegel (1986) established the value of waiting in investment timing.[9] Then, investments under volatile market conditions (e.g., fluctuating electricity prices) can be characterized as an optimal stopping problem. Firms will then adopt a threshold policy where investment occurs when distinct price levels are reached. Such an investment behavior can be used to describe customer model evolution over time. Concerning energy efficiency investments, Hassett and Metcalf (1993) argue that this option value of flexibility may be a reason for underinvestment in energy efficiency.

Strategic Investment Besides being exposed to market uncertainty, smart grid investments are typically competitive in the sense that their viability may depend on the actions of other market participants. For example, an increasing number of decentralized storage systems may dampen the price spreads eroding the economic profitability of all storage systems (cf. Ahlert and Block, 2010). Therefore, smart grid investment policies should dynamically depend on the system state. This competitive interaction may lead to strategic preemption among competing entrants. Therefore, adoption may occur faster in a competitive situation. On the other hand, second-mover advantages (e.g., technological spillover) may reduce the adoption speed in dynamic markets (Mason and Weeds, 2010).

Chevalier-Roignant et al. (2011) identify a set of industry and investment properties that managers need to factor in when devising strategic investment strategies. Out of this set I want to highlight factors that may be of special importance for smart grid investments:

- *Lumpiness of investments* Larger capacity increments will slow down investment activity. In the smart grid this could mean that offering a greater variety of smart grid solutions (e.g., smaller storage systems, different CHP sizes) to retail customers may increase adoption of such technologies. This can also be seen as an argument for group formation to reduce individual contribution requirements. Such smart grid investment cooperatives would be analogue to the generation and consumption cooperatives described by Chalkiadakis et al. (2011).

[9] Dixit and Pindyck (1994) provide a comprehensive treatise of the theory of investment under uncertainty.

- *Load Flexibility* Smart grid investments aim to be facilitate demand and supply side flexibility. This flexibility helps mitigate the externalities imposed by volatile market prices. Given the interaction between multiple self-interested agents aggregate demand and supply are more volatile in more competitive markets. Therefore, smart grid investments enhancing load flexibility will thus be more valuable in such markets. Hence, market liberalization and fostering of smart grid investments go hand in hand.

- *Hybrid investments* Platform investments give rise to two stages of competition — initial platform (standard) adoption and subsequent market competition. Large uncertainty in the first stage (missing standards, quick technological change) may slow down first stage investments and thus hinders reduce second-stage innovations. Smart meters are central to enabling smart grid functionality. However, standardization and financing issues currently stand in the way of their roll-out. This significantly dampens innovation and investment in subsequent technologies.

- *First-mover advantages* Direct advantages for initial investors will unambiguously increase adoption speed. However, under competitive subsidy schemes (e.g., establishing global cap levels) investment may occur too early from a welfare perspective, that is before technology matures sufficiently or market prices reach a sufficiently high levels. Feed-in subsidies have a long tradition for investments in PV installations and purchase incentives have been discussed for EVs as well. The market has seen subsidies being reduced over time and a corresponding building boom prior to reduction dates (Hübner et al., 2012). Careful analysis of such effects induced by granting first-mover advantages should guide future subsidy policies.

Smart grids will profoundly alter the economics of power systems by increasing competition through integration of a greater variety of economic agents (prosumers, micro-generation, storage operators) as well as by establishing greater flexibility levels. These changes challenge traditional investment evaluation techniques. This is an important insight for both investors as well as regulators.

3.5 Discussion

The increasing intermittency of generation increases the importance of demand side participation in the future power system. To assess aggregate potentials of flexible demand as well as technology describes diffusion dynamics appropriate customer models are required. This chapter proposed a principled approach for modeling customers in the smart grid. The remainder of this thesis focuses on the first three levels discussed in this framework and aims at achieving a better understanding of flexible demand as demanded by Varaiya et al. (2011).

Still, questions concerning the dynamics of adoption and diffusion of smart grid capabilities are of great importance as well. Therefore, future research is required to evaluate the proposed techniques and derive corresponding regulatory recommendations.

Part II

Modeling and Coordinating Residential Loads

Chapter 4

Customer Modeling Using Smart Meter Data

Within distribution grids, residential and small business customers (annual consumption below 100,000 kWh) constitute a significant load share. Concerning total load, these customers account for approximately 40% of the total load (see Table 2.1). This customer segment has so far hardly been integrated in DSM activities. However, it is a central goal to increase their role in the future power system (Faruqui et al., 2010). Given the absence of real-world DSM implementations, recent smart grid research has aimed at assessing the flexibility potentials of households using bottom-up models (Paatero and Lund, 2006; Gottwalt et al., 2011). These models confirm the DSM potentials but critically hinge on several assumptions (device usage patterns, household equipment) and are limited to households. Furthermore, the overhead of bottom-up modeling for a large number of relatively small loads seems unwarranted. Therefore, a granular representation of small customers using a top-down approach based on real-world load data is desired.[1]

The key to this approach is smart metering data which facilitates customer segmentation based on dynamic load patterns instead of mere load totals. Using Data Mining (DM) clustering techniques, distinct customer groups can be identified. A load profile clustering analysis was developed, implemented and evaluated in cooperation with ENERGY4U GmbH[2] and Allgäuer Überlandwerk (AÜW)[3]. While this cluster analysis approach facilitates top-down customer modeling, the main use cases for the industry partners are the design of segment-specific rates (Ramos and Vale, 2008; Ighli et al., 2012) and improved forecasting capabilities (Räsänen and Kolehmainen, 2009).

In the following I describe the implementation and evaluation of the smart meter data cluster analysis. A software artifact was created following the design science approach as outlined by Hevner et al. (2004): First the problem relevance and the related literature are addressed. Subsequently, I describe the technical and methodological realization as well as the evaluation using real data. Finally, the integration of load response capabilities is discussed.

[1] This chapter was previously published as a research paper (Flath et al., 2012).
[2] Energy4U is an IT consulting firm for SAP solutions in the utilities sector (`www.energy4u.org`).
[3] Allgäuer Überlandwerk is a regional utility based in Kempten. (`www.auew.de`).

4.1 Problem Relevance and Related Work

New regulatory requirements, a changing public opinion towards the energy system, technological change and increasing resource scarcity are the main drivers of change for the energy sector. Responsibilities and tasks that were traditionally performed by a single integrated company are getting split up and distributed. This unbundling and the development of new market roles changes the electricity value chain and creates opportunities for new entrants. The introduction of smart meters may result in another paradigm change — especially in the areas of customer and portfolio management.

Since power-based (in contrast to energy-based) load measurement is already common practice for large industrial customers, a particular challenge of a large-scale smart meter roll-out involves the design of business processes for many small customers and the handling of the associated large sets of micro-data. Performing a customer segmentation based on consumption data potentially reveals characteristic customer load profiles within the heterogeneous population. This provides electricity suppliers with an in-depth overview of their customer portfolio and at the same time allows easy data interchange with other corporate Information Technology (IT) systems like Enterprise Resource Planning (ERP) or Customer Relationship Management (CRM) solutions.

4.1.1 Business Intelligence and Knowledge Discovery

Business Intelligence (BI) has emerged as the standard way to process large data sets into information and business-relevant knowledge in corporations (Cody et al., 2010). Through IT-based data access, analysis and processing BI supports decision makers handling data-intensive problems (Strauch and Winter, 2002). BI itself is not bound to a specific system, in fact a diversity of information retrieval and analysis systems can be applied. Kemper et al. (2004) suggest a classification of these systems into ad hoc and model-driven systems. In this work, the focus lies on the model-driven analysis in line with Knowledge Discovery in Databases (KDD) as established by Fayyad et al. (1996). KDD refers to the overall analysis process consisting of data preparation, data mining and reporting. Within this process, data mining is the actual tool identifying and extracting previously unknown and potentially useful patterns from the data (Han and Kamber, 2006; Bissantz and Hagedorn, 2009). The knowledge generated in this process can be used, for instance, in decision support systems (Kemper and Baars, 2006) or reporting tools. In recent years, the Cross Industry Standard Process for Data Mining (CRISP-DM) reference model has emerged as a quasi-standard for KDD tasks (Kurgan and Musilek, 2006; Shearer, 2000). Herein, the starting point for the data analysis is determined by business problems and tasks which are systematically addressed in six process phases (Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, Deployment).

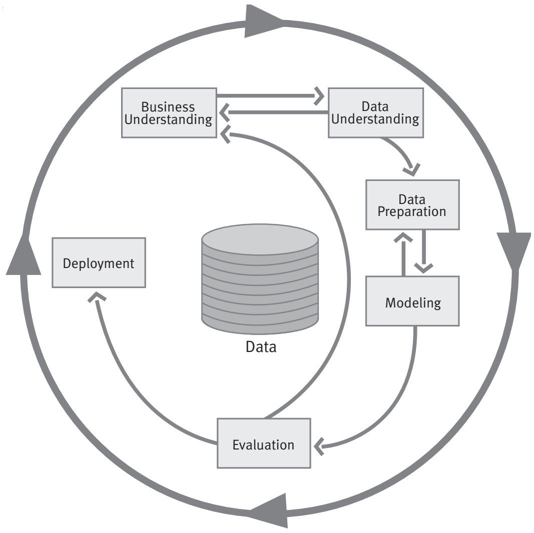


Figure 4.1: Phases of the CRISP-DM reference model (Shearer, 2000)

4.1.2 Data Mining in the Electricity Sector

The advancing liberalization of energy markets and the rising availability of consumption data have recently spotlighted data mining approaches to analyze load profile data. Pitt and Kitschen (1999) and Ramos and Vale (2008) study the applicability of different clustering techniques for the classification of large industrial clients' daily power consumption. Espinoza et al. (2005) consult the cluster analysis to scrutinize the daily and weekly load data delivered from transformer substations. Figueiredo et al. (2005) develop a procedural model to cluster and classify power customers which is then used for the analysis of customer data on the distribution network. Gerbec et al. (2002) consider consumption profiles of business customers and extract different types of typical load profiles. They propose and test different methods of clustering, where average consumption values are used.

Varaiya et al. (2011) note that sensors and smart meters will provide system operators with more detailed information on the power system state. With respect to the consumption data, electricity providers can use the revealed information patterns to improve their business processes. For instance, Chicco et al. (2003) study the margin opportunity in the design of optimized tariffs for identified customer clusters. Espinoza et al. (2005) develop forecast models based on customer clusters on the distribution network. Given the increasing adaption of smart grid technologies it is hardly surprising that Keshav and Rosenberg (2011) as well as Ramos and Liu (2011) underline the central importance of data mining techniques for the transformation of the electricity system.

4.2 Cluster Analysis of Load Data

As mentioned above, DM techniques offer a methodically sound approach to analyze load profiles. Furthermore, they offer a variety of potentials for application in the energy industry. However, its actual implementation within corporations requires a suitable technical realization. In doing so, processes and systems in the energy industry as well as the peculiarities of the smart metering landscape have to be taken into account. In the following, I will briefly describe the technical and methodical design decisions that underlie the cluster analysis implementation.

4.2.1 System Environment and Analysis Process Design

The cluster analysis was realized within the data warehouse software SAP NetWeaver Business Intelligence (SAP BI) as this system was already used by the project partner. However, this decision actually increases the practical relevance of the work since SAP BI is applied in various mid- and large-sized corporations in the electricity sector. Still, the concrete analysis methods are independent of the chosen platform and can be implemented in any other KDD-package.

In the pilot implementation a three-phase analysis process roughly following phases three to five of the CRISP-DM reference model (see Figure 4.2) was chosen: First the raw load data is prepared by performing error correction and transforming it into the appropriate format. Next DM tools are applied to achieve the desired clustering results which are then deployed and evaluated (for an extensive process overview see Figure C.1 in the Appendix).

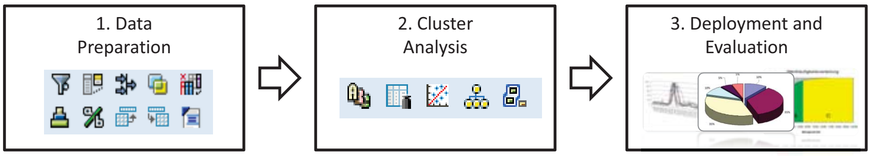


Figure 4.2: Phases of Cluster Analysis Implementation

4.2.2 Data Preparation

Data preparation for the cluster analysis is a crucial step of the KDD process. At first, the integrity of the raw data has to be assured through filtering and construction of repair values. Thereafter, the data is converted to the format required by the cluster analysis.

Data Cleaning Data transmission in smart metering systems usually spans a multitude of technical components (e.g. smart meter, data concentrators, gateways, etc.). If one of these components fails, corrupted values or recording gaps are likely to occur. Clearly, such data faults need to be avoided to guarantee integrity of the analysis. In order to interpolate time series of consumption data, literature proposes different approaches. For instance, Ramos and Vale (2008) apply artificial neural networks while Figueiredo et al. (2005) rely on a regression approach. Both approaches rely on comprehensive preliminary operations on a given load data set and are thus not applicable to handle general load data sets as required for a generic online implementation. For the most part, the analyzed data set exhibits only singular corrupted values (the smallest time segment equals 15 minutes). Therefore, a simple linear interpolation approach for data cleansing was chosen. This lightweight

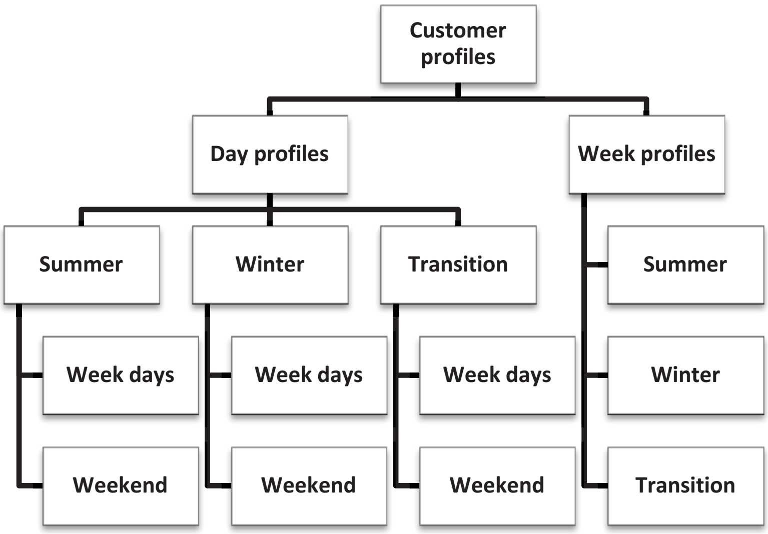


Figure 4.3: Cluster analysis scenarios

approach achieves robust results for minor data gaps. However, it cannot reliably estimate major data gaps. Therefore, daily records with recording gaps exceeding one hour were discarded.

Clustering Scenarios In case of volatile consumption patterns, the arithmetic mean does not entirely capture the customers' behavior. Academia proposes two approaches to cope with this issue. On the one hand, Räsänen and Kolehmainen (2009) extend the clustering objects by additional data points (e.g., standard deviation or skewness of the 15-minutes consumption). Ramos and Vale (2008) introduce a segmentation of the analysis days (weekday, season) which separates the raw data sets into more homogeneous subsets. As the load profiles with 15-minutes segments already give rise to very large data objects, a segmentation approach suggested by Ramos and Vale (2008) was chosen in order to sustain scalability. For the data preparation, the characteristic load profiles for nine "cluster scenarios" can be assembled from cluster type (week, weekday, weekend) and season (summer, winter, transitional). The described segmentation is illustrated in Figure 4.3. This approach allows for a simple benchmarking with the standard load profiles utilized by the German energy industry which distinguish between similar day types (BDEW, 2010; Gottwalt et al., 2011).

Load Profile Normalization Using the arithmetic mean over all observations, the (scenario-specific) average load profile vector for each smart meter data set is derived. However, these average load profiles cannot readily be compared against one another due to varying absolute load levels. To achieve comparability independent of the load level the data needs to be normalized(Han and Kamber, 2006). This is achieved by means of a normalization function $\sigma(X)$ which transforms an absolute load profile vector X to a relative normalized one X', that is

$$X' = \sigma(X) \tag{4.1}$$

As load data profiles represent a collection of the same measurement variable over time, the different dimensions of the load vector should be equally weighted. Then the normalization function trivially obtains by scaling with the load profile's maximum value, that is

$$\sigma(x_i) = \frac{x_i}{\max\limits_{j=1..|X|} \{x_j\}}. \tag{4.2}$$

Based upon this normalized load curve $\sigma(X)$, a characteristic load profile per time period (one day or one week) can be determined for each smart meter data set.

To complete the data preparation phase, the clustering data can be enriched with further information that is available in other IT systems (e.g. ERP or CRM data). Such a linkage of data can guide and support the subsequent analysis. However, in the present work such cross-validation was not possible due to data usage restrictions.

4.3 Cluster Analysis Implementation

A cluster analysis aims at discovering structures in large data sets. According to Rodrigues et al. (2003), the *k*-means algorithm and a combination of *k*-means and artificial neural networks are suitable approaches for the clustering of load profiles. Both approaches achieve a similar clustering performance in the handling of customer load profile. The *k*-means algorithm is considered to be the best known and most frequently applied partitioning clustering technique (Vercellis, 2009). Therefore, it is implemented as a standard algorithm in most of the established data mining software (also in SAP BI).

4.3.1 k-Means Clustering

Given its robustness and wide availability in DM packages, only the *k*-means algorithm was used for the following analysis. The *k*-means algorithm (see Algorithm 4.1) works iteratively: It divides the data set into k clusters by minimizing the sum of all distances to the respective cluster centers. The algorithm does not guarantee a global optimum (Beringer, 2008). He notes that it is hence important to randomize initialization values in order to achieve better results by covering a larger search space.

Furthermore, the choice of the number of clusters k is a crucial algorithm input influencing the clustering quality. The proper number of clusters is not known ex ante, therefore, the cluster analysis is initially conducted with all cluster numbers that are to be considered. Subsequently, the results of the various starting values and the number of clusters are rated with respect to their performance in order to identify the best clustering.

Algorithm 4.1 k-Means Clustering with n data objects

set k
for $i = 1 \rightarrow k$ **do**
    DetermineInitialClusterCenter(k)
loop
    noChange = True
    for $i = 1 \rightarrow n$ **do**
        $r =$ CurrentAssignment(i)
        $s =$ BestAssignment(i)
        if $s \neq r$ **then**
            CurrentAssignment$(i) = s$
            noChange = False
    if numberOfIterations > maxIterations $\vee$ noChange **then**
        Terminate
    for $i = 1 \rightarrow k$ **do**
        DetermineClusterCenter(k)
    numberOfIterations++

4.3.2 Clustering Evaluation

In order to numerically evaluate the cluster quality, literature proposes, for instance, the Clustering Dispersion Indicator and the Mean Index Adequacy Indicator (Ramos and Vale, 2008; Rodrigues et al., 2003). Both indicators have in common that they are monotonically increasing with the number of clusters. Thus, they are not suitable for a simultaneous determination of the optimal number of clusters. Davies and Bouldin (1979) propose a cluster evaluation index which does not exhibit this property. The Davies-Bouldin Index (DBI) is given by

$$DBI = \frac{1}{k}\sum_{i=1}^{k}\max_{j\neq i}\frac{S(C_i)+S(C_j)}{d(C_i,C_j)}, \tag{4.3}$$

where $S(C_i)$ denotes the average distance between data objects and the cluster center in cluster C_i and $d(C_i,C_j)$ denotes the distance between the centers of clusters C_i and C_j.

The DBI evaluates the clustering quality based on the sum of the fractions of the variance within two clusters and their centers' distances and weighs this value against the total number of clusters.[4] The identification of local index minimums thus allows for the determination of a suitable number of clusters. For the search, only the basic domain needs to be indicated. This is typically given by the application context. It is not unlikely that different cluster numbers are chosen for different application contexts (e.g., customer modeling, tariff design, load forecast). In this work's technical realization, the DBI has been modeled and integrated in the Analysis Process Designer (APD). Moreover, the Silhouette Index (Rousseeuw, 1987) and the index proposed by Dunn (1974) were included as additional measures for evaluating the quality of different clustering results.

[4] As such, it follows the spirit of information criteria aiming for model parsimony.

4.4 Evaluation of Clustering Results

After selecting the final cluster specification, the results need to be processed for business applications. This is realized through appropriate reporting as well as automatic exchange with other applications, e.g., decision support or CRM systems. In the presented pilot implementation, the results were visualized using the SAP analysis- and reporting tool BEx Analyzer which is embedded in Microsoft Excel. The BEx analyzer provides capabilities for both graphical and tabular reporting. Figures 4.4, 4.5 and 4.7 show that the clustering approach facilitates a homogenous customer segmentation based on daily and weekly load profiles: One can identify customer groups with distinct load profiles.

4.4.1 Day Profiles

In the analysis scenario weekdays (winter), load data from 215 customers was analyzed. This analysis yielded a configuration with 14 clusters (Figure 4.4).[5] In contrast the scenario weekend days (winter) yielded only 10 clusters (Figure 4.5). The differing number of clusters indicate a lower diversity of weekend load profiles. Some of the profiles (e.g., cluster 11) only exist during the week which is typical for enterprises. Moreover, one can see a convergence of household consumption behavior on weekend days. This confirms the scenario-based clustering approach. Another characteristic difference between weekday and weekend clusters is the consumption distribution over the day. Weekdays exhibit a large share of consumption on mornings and evenings, while weekends exhibit a more homogenous consumption distribution.

[5]Additional information on the weekday clusters is provided in Table C.1.

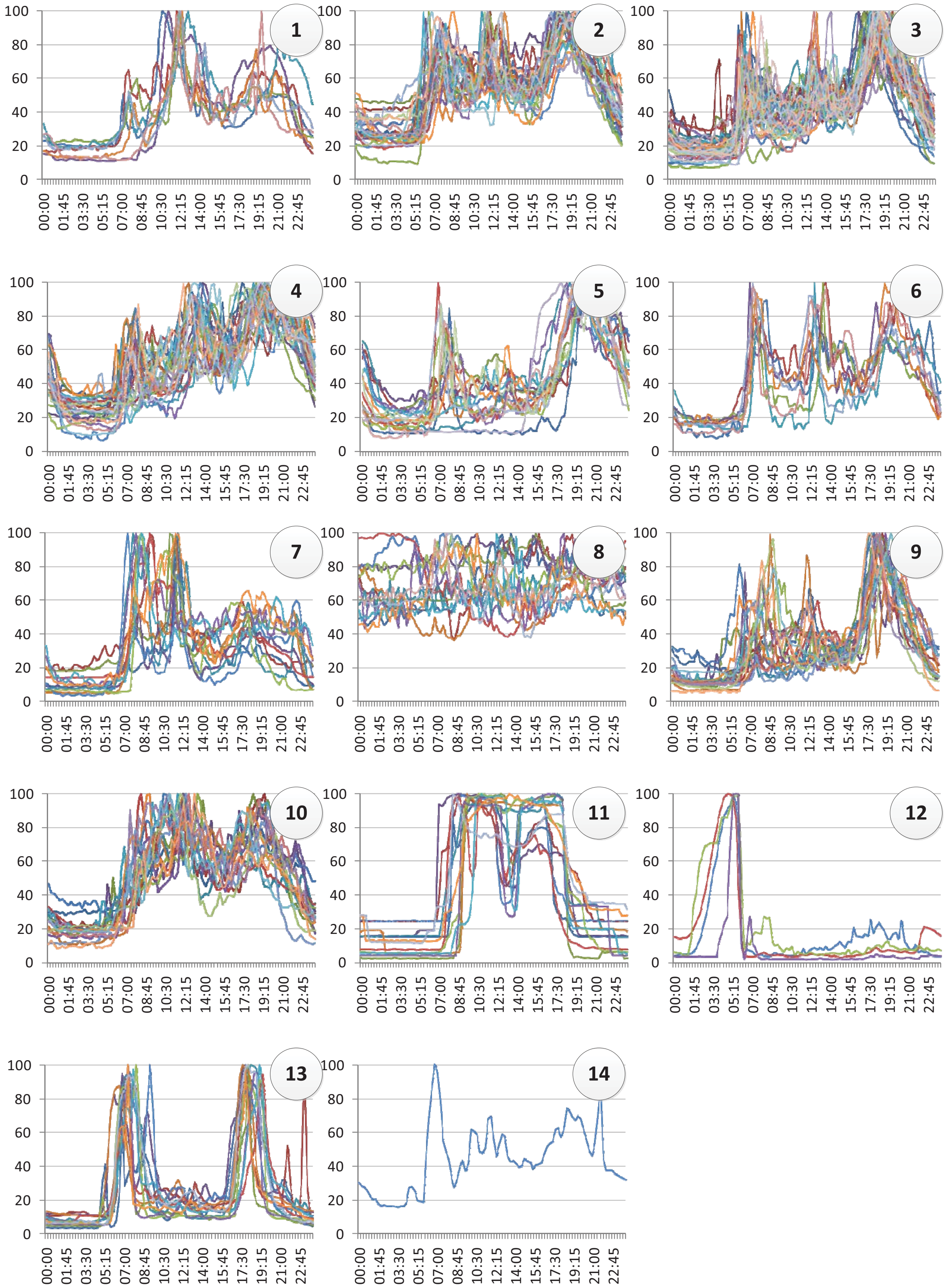


Figure 4.4: Clustering results – Day profiles (Workdays, Winter)

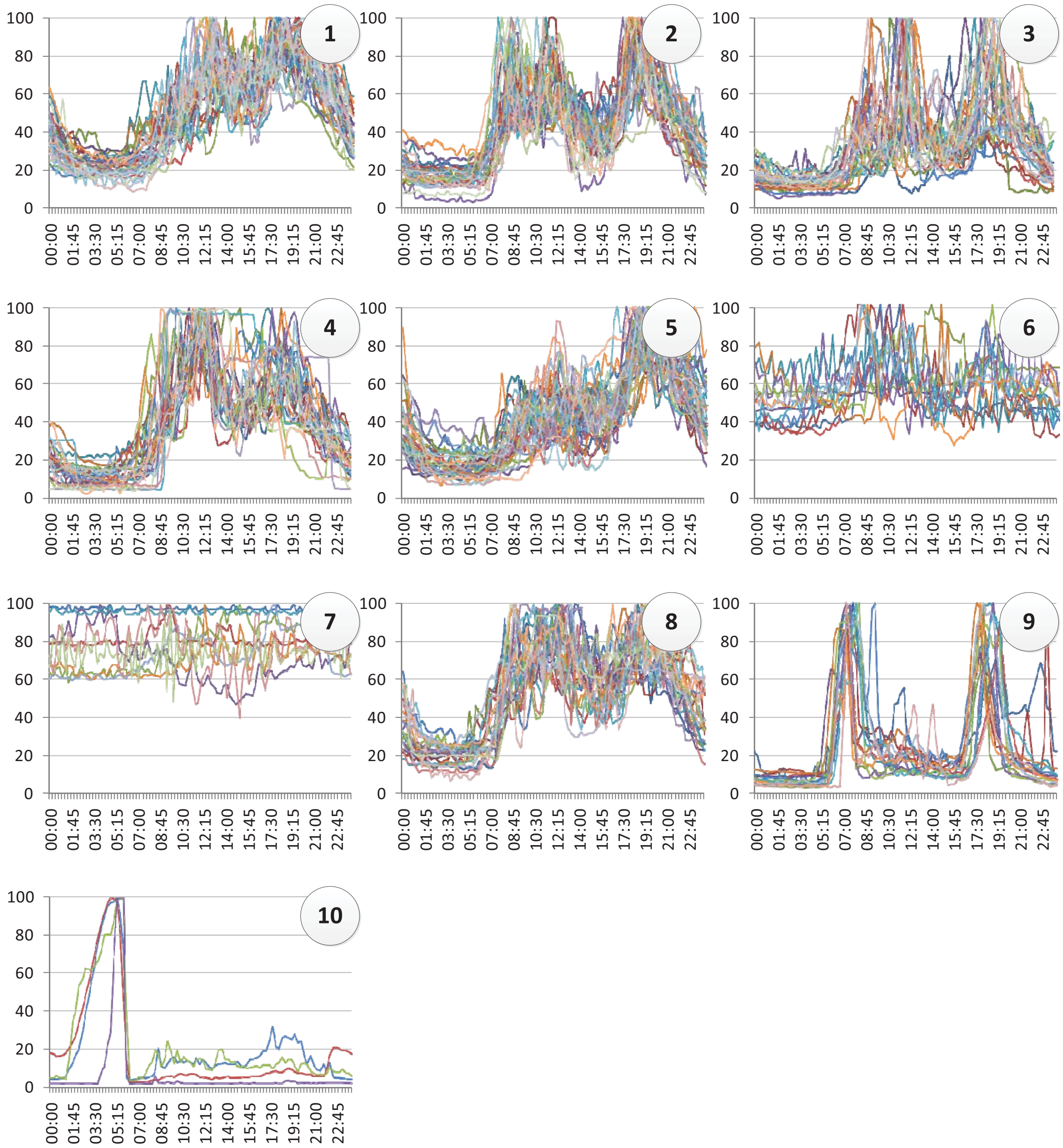


Figure 4.5: Clustering results – Day profiles (Weekend, Winter)

4.4.2 Customer Type Identification

As the clustering is solely based on consumption data, the adequacy of the clustering results can be evaluated by trying to determine each clusters' predominant customer type. The German standard load profiles provide a natural benchmark for this type of evaluation on daily load profiles (Figure 4.6).

The clusters 11, 12 and 13 show distinct similarity with the standard load profiles for businesses (11), heat pumps (12) and farms (13). These assumptions are also supported by the absolute consumption levels. On the other hand the clusters 1-6, 10 and 14 with average annual consumption of about 3,600 kWh are most likely exclusively composed of private household customers. The diversity of these household clusters and their large difference to the German standard household load profile H0 show that cluster analysis of smart metering data can facilitate a more granular customer characterization. For instance cluster 5 exhibits a comparatively high consumption share during evening and early night hours. Given the similarity with cluster 9, the challenge of determining a clear distinction of such micro-segments becomes evident. For clusters 7, 8 and 9 the type assessment is less clear suggesting that they are most likely composed of different customer types. Extending the consumption data with additional information may facilitate better differentiation of these clusters and thus improve the clustering results.

4.4.3 Week Profiles

The week (winter) load profile scenario yields a grouping with 16 clusters. Due to their repetitive structure a graphical distinction between the different clusters is more difficult than in the case of single day load profiles. However, we can again spot distinct patterns (especially clusters 10, 13 and 15). At first glance the consumption ratios between different days as well as the periodicity of the load development seem fairly homogenous. The main exceptions are clusters 8 and 9 which exhibit distinctly lower consumption on weekends with Sunday consumption levels being even lower than on Saturday.

4.5 Customer Modeling using Cluster Results

While labeling of the diverse clusters may be difficult, they can still be used as the base for modeling a heterogeneous customer population with a large number of micro-segments. Then, each cluster represents a micro-segment and one can then directly apply the clusters' representative load curves to obtain simple static customer models with constant demand levels as indicated by the clusters' characteristic load curves. To appropriately reflect the customer population, the size of these models should be chosen according to the number of profiles represented by the cluster. Furthermore, to account for individual size differences (e.g., large family vs. small family) within customer segments, one needs to consider that the clustering occurs on the basis of relative load profiles.

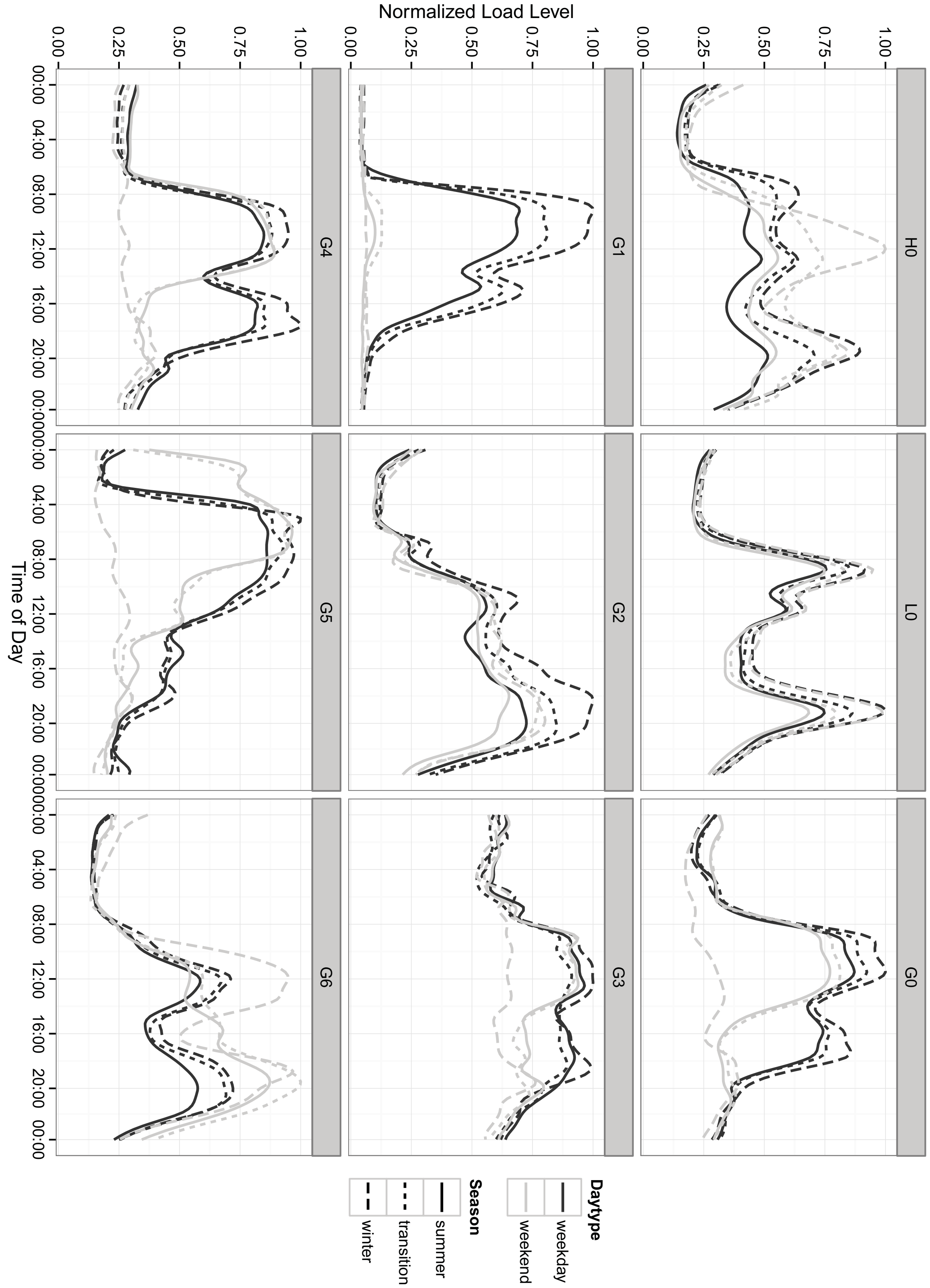


Figure 4.6: BDEW Standard Load Profiles (BDEW, 2010)

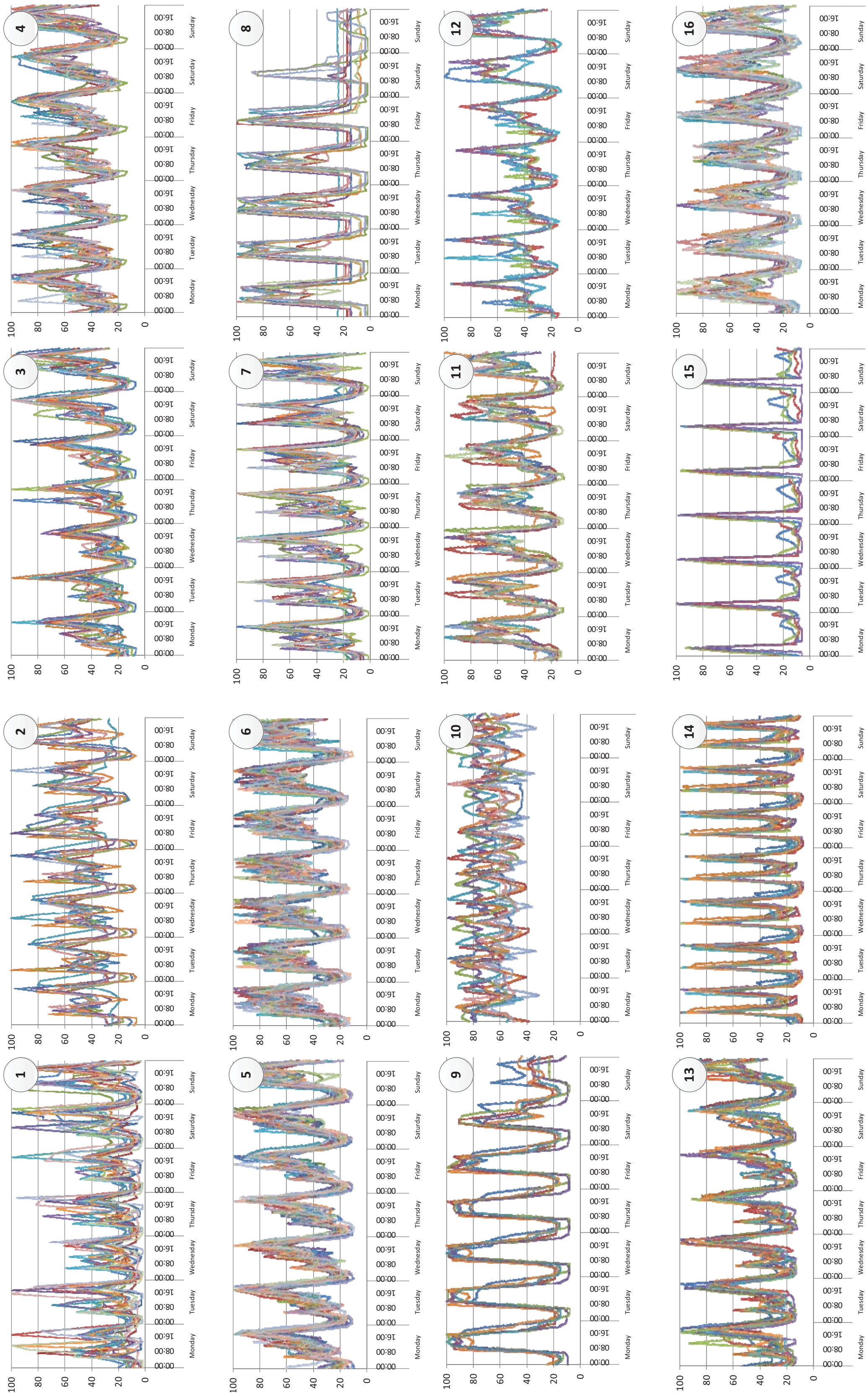


Figure 4.7: Clustering results – Week profiles (Winter)

Cluster analysis of load data provides us with a representation of static customer characteristics as required in the first level of customer modeling (Chapter 3). However, as noted before, such static load behavior is not sufficient for pursuing meaningful smart grid analysis. For customer models to interact meaningfully, the static characterization needs to extended in order to reflect their dynamic load behavior.

4.5.1 Behavioral Load Curve Interpretation

A cluster's representative daily load curve describes a customer group's electrical energy consumption over the course of a day. Trivially, peaks represent times of the day where *on average* this customer group consumes electricity more often than at non-peak times. Note, that if device-level load curves were available these could be directly interpreted as frequency diagrams for device usage at a given time. Consequently, load curves are greatly shaped by a customer segment's typical activity times as well as appliance usage patterns. Given this observation, a customer segment's average load curve under a traditional linear electricity rate can be interpreted as a revealed preference (cf. Esser et al., 2007) for device usage timing. Therefore, a change in the load curve represents a move away from the most preferred consumption timing and as such must be induced through appropriate (monetary) incentives. Similarity of load curves is then an initial measure for the likeliness of an alternative consumption plan. However, the aggregate load level may be too coarse to identify the underlying usage diversity: An average value of 1kW at noon could indicate a total load of 1kW always active or a load of 10kW active 10% of all times.

Load Quantile Characterization Realizing that a customer's load profile is not captured by a single time series (e.g., the average value) but rather by a collection of such observations over the course of a longer interval (e.g., one year), a more differentiated analysis is required. One can recover some of the underlying usage diversity information by looking at load quantile levels instead of the absolute load curve level: The 0%-quantile represents the amount of energy that is at least consumed in any case, that is, in 100 percent of all days, or the minimum consumption for a given hour. Following this scheme, the x percent quantile represents the x percent lowest consumption observations, that is, the amount of energy which is at least consumed in $100 - x$ percent of all days. Finally, the 100 percent quantile denotes the maximum consumption for a given time interval.[6] Figure 4.8 illustrates this approach and shows that there are obvious differences in the occurence regularity of certain load levels. This load level variance can be interpreted as load flexibility as the customer segment does intrinsically vary its consumption level at the given time of the day. Similarly, one can also identify loads that are highly intrinsic to the given customer, namely the ones that exhibit 0.25 quantile levels close to the average load level as can be seen during nighttime. These "sticky" loads can be interpreted as highly inflexible. However, one problem with this approach obtains from automatic loads present in the historic load pattern — e.g., the night-time heating loads in cluster 12 in Figure 4.4. These would incorrectly be classified as fixed loads while they

[6]Note that each load quantile requires a separate data set. To maintain scalability (cf. Section 4.2.2) and also to guarantee distinctiveness I want to limit the number of quantile levels used.

are actually highly flexible because they occur in an arbitrarily scheduled fashion so far. Therefore, the presence of automatic loads needs to be accounted for when assessing load flexibility from quantile load levels.

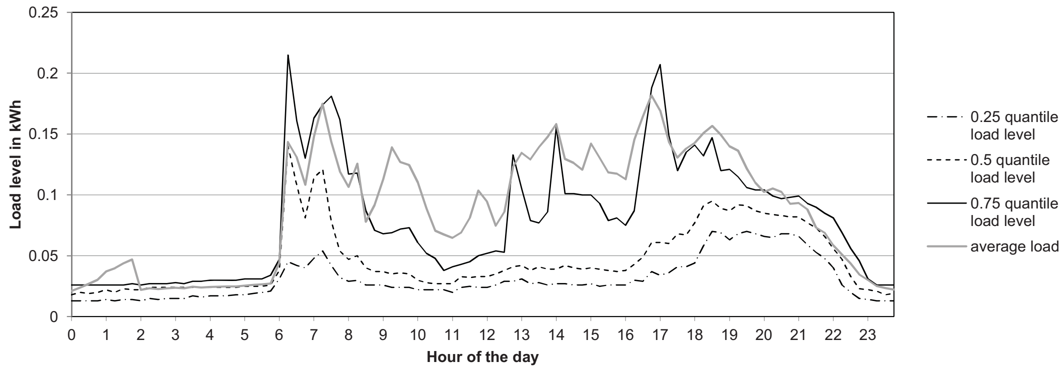


Figure 4.8: Exemplary load quantile levels

Load Type Differentiation The more intrinsic ("sticky") a pattern in the demand curve is to the load behavior of a customer segment, the more likely it is expected to occur at lower quantile-levels — that is, more often over the course of the observation period. This empirical pattern can be interpreted as different load flexibility types when applying appropriate quantile levels. Limiting the observation to three quantile levels (which also preserves scalability) the approach aligns well with Wang et al. (2010) who categorize energy consumption into three distinct flexibility types[7], *fixed*, *shiftable* and *avoidable* consumption:

- *Fixed loads* — certain electricity consumption decisions in a customer are fixed, i.e. not movable to a different time slot or avoidable at all. Hence, this type of consumption will not adjust to power prices. Typical examples for this load class are lighting, cooking and electronic entertainment devices.

- *Shiftable loads* — certain electricity consumption decisions in a customer have to occur at some point in time over the course of the day but the exact timing may be chosen freely to some extend. As stated in the introduction, consumption choice under a flat tariff is a revelation of customer preferences and hence any change from this preferred consumption timing will come at a utility cost for the household. Typical examples for this consumption type are washing machines, dryers as well as charging of major appliances, e.g., electric vehicles.

- *Avoidable loads* — for certain consumption types consumers can choose different operating levels, e.g. AC or heating. This allows the customer to respond to a price vector by curtailing or expanding consumption.

Using the load quantile approach I attach different quantile levels to determine the corresponding share of these different load types over time. Exemplary, one

[7]This approach is common to a variety of papers, e.g., Chang (1988), Schweppe et al. (1989) or Gottwalt et al. (2011).

could define the 0.25 load quantile as the threshold for fixed loads and the 0.75 load quantile as threshold for shiftable loads. These exemplary threshold levels are as such arbitrary.[8] Clearly, their careful choice is key to a meaningful characterization of demand response behavior. While a proper evaluation would be desirable it is hard to realize with aggregate data set. However, using a variety of threshold levels an appropriate sensitivity analysis of the results can be obtained.

Having determined the threshold levels, the average load at a given time can be allocated accordingly to the flexibility levels. Following Carpaneto and Chicco (2008) one can then further generalize the approach by using parameterized statistical distributions instead of historic averages.

4.5.2 Characterizing Demand Response

Having established the relative higher importance of low-quantile-levels, it is straightforward to concede a higher relative value to this consumption. It can be assumed that the degree of difference between a given, genuine consumption profile and an adjusted one (e.g., for time dependent prices) is correlated with the disutility induced by this adjustment. Understanding the "cost" of changing from a consumption plan to another is the key component for building a demand model that captures intra-day load shifting and shedding. It can be intuited that this disutility is composed of avoidance and shifting disutility. While the former essentially captures well-known price elasticity effects, the latter is a unique part of the electricity consumption problem. Following Wang et al. (2010)'s notion of fixed, shiftable and avoidable loads the parameters for the two disutility components are readily determined: Fixed loads have infinite shifting and shedding disutility, flexible loads have finite shifting and infinite shedding disutility while for sheddable loads both components are finite. Besides, maximum shifting distances and other operational constraints need to be accounted for (Mohsenian-Rad and Leon-Garcia, 2010).[9]

Customer consumption choice then needs to balance cost as described by the vector of hourly prices against the disutility from changing the revealed preferred consumption plan under a flat tariff. Given the discrete time structure derived from the price vector, the corresponding household optimization model is readily constructed in a similar fashion as the linear optimization problem used by Esser et al. (2007) or the mixed integer program used by Sou et al. (2011).

4.6 Discussion

The broad roll-out of smart meters poses significant challenges to electricity utilities. On the one hand large investments in the metering infrastructure are required and on the other hand traditional business processes need to be redesigned. Through processing and utilization of customer consumption data from smart meters electricity companies may be able to achieve big efficiency gains. This chapter presented an

[8] As is the number of flexibility classes proposed by Wang et al. (2010).

[9] Given the lack of tariff data, these costs cannot be properly characterized. To avoid arbitrary assumptions I only sketch the general approach.

implementation and evaluation of a cluster analysis approach for smart meter data within a business intelligence environment. Using DM techniques one can extract distinct customer segments from smart meter load data. By creating a pilot implementation within a business intelligence environment of a regional utility we were able to demonstrate the applicability in practice. Given a direct integration with existing IT systems (e.g., ERP or CRM) this clustering approach is relevant for metering service companies as well as utilities. Based on the cluster analysis metering service companies can offer innovative service products like energy management planning or regional load profiles. Suppliers can profit from the possibility of designing segment-specific rates (see Chapter 5). The combination of data-driven customer clustering and the quantile-based provide an initial solution to the challenge of "how to aggregate demand response of individual consumers into a probabilistic demand curve" (Varaiya et al., 2011).

4.6.1 Limitations

The presented analysis used the workhorse k-means algorithm to demonstrate the possibility of extracting information from smart meter consumption records. Utilization of more sophisticated clustering techniques (e.g., neural networks or self-organizing maps) may further increase clustering quality. Additional limitations arise from restrictions of the employed data set and the absence of dynamic rates. Therefore, it was impossible to extract or evaluate price elasticity values of the identified clusters. This would be a central asset for rate design tasks based on the clustering results. Similarly, while the introduction of different analysis scenarios increased cluster homogeneity, it also gives rise to a multitude of potential cluster combinations that may serve as a basis for subsequent decision support tasks. A central challenge in this process is the selection of an appropriate base scenario to determine the most relevant clustering. However, the cluster analysis results indicate that different individual customer mixes constitute the different cluster populations across the different analysis scenarios.

4.6.2 Future opportunities

The cluster analysis gives rise to subsequent research questions. To validate the robustness of the identified clusters regionally and temporally additional data sets are required. Moreover, the integration of additional data sources such as current electricity rate information, or household properties such as demographic data can be leveraged for better segmentation. Following Newsham and Bowker (2010), there is an insufficient understanding to what extent households adapt their load behavior given their socio-economic properties. As this is a central question for future demand-centered control paradigms, future research needs to focus on assessing load shifting potentials and demand elasticity values. Based on such richer data sets, static household models can be enhanced using the quantile-based analysis of the load curves. Moving away from average values and acknowledging load variance patterns, additional flexibility information can then be extracted from the raw data. This can be used to implement demand response capabilities in top-down models using the approaches described by Esser et al. (2007) and Wang et al. (2010). Furthermore, alternative clustering techniques and selection procedures could be tested to ensure the robustness of the results.

Chapter 5

Customized Time of Use Rate Design

The availability of detailed customer models (Chapter 3) not only improves the forecasting ability for loads in the power system, it also enables the design of appropriate coordination mechanisms. For retail electricity customers equipped with smart metering infrastructure, the development of optimized dynamic retail electricity (Chapter 2) rates is a promising avenue offering great business opportunities for utilities as they allow improved price discrimination and facilitate the reduction of peak loads. Their importance in the electricity sector is described, among others, by Parmesano (2007).[1] By influencing the demand side, dynamic electricity rates can improve system efficiency. Furthermore, time-differentiated billing allows greater transparency with respect to the impact of generation costs for the formation of retail electricity prices. Therefore, they achieve an increased coupling between costs and prices which improves the fairness of retail electricity pricing (Faruqui et al., 2010).

Given the identification of distinct customer segments (see Section 4), segment-specific rate design with individual time-variable rates for each customer segment are of special interest. This allows better consideration of heterogeneity in consumption behavior while avoiding the complexity of rate design on the individual customer level. Furthermore, it provides a natural workaround for the avalanche effect put forward by Gottwalt et al. (2011) — if customer rates are heterogeneous, over-coordination may be less problematic than in a scenario with population-wide rates. In the context of customer-specific rates, I want to focus on TOU rates. While it is known that TOU rates are less efficient than RTP pricing approaches (see, e.g., Bohn, 1982), Borenstein (2005b) stresses the fact that TOU pricing is structurally easier to understand and has thus attained wider acceptance. This view comports with Celebi and Fuller (2007) who note that "TOU pricing can reduce the inefficiency of single pricing while being more practical [...] than real-time pricing". Woo et al. (2008) argue that attaining customer acceptance is key to realizing a successful DSM implementation. Similarly, Dütschke and Paetz (2013) show that customers are hes-

[1] One can also find application scenarios in other domains. Fore example, Saure et al. (2010) apply TOU rates to improve the utilization of cloud computing services.

itant to adopt too complex rates. Therefore, I want to develop a structured way to derive segment-specific TOU rates.[2]

5.1 Time of Use Design Requirements

The design of segment-specific TOU rates requires determining the relevant endogenous parameters for each customer segment depending on its load curve. I leverage the load profiles described in Chapter 4 to develop the rate specifications. While such load profile-based rate design has been applied before (e.g., Chicco et al., 2003; Panapakidis et al., 2012), the literature so far does not provide a coherent and principled approach for determining TOU rates.

Unlike under a RTP regime, where the rate specification can follow fairly arbitrary patterns and price levels are determined individually, a valid TOU rate structure, characterized by a set of rate zones, needs to additionally reflect underlying rate requirements, the most important ones being:

- the number of rate zones,
- the start as well as end times of the rate zones, and
- the price level of the rate zones.

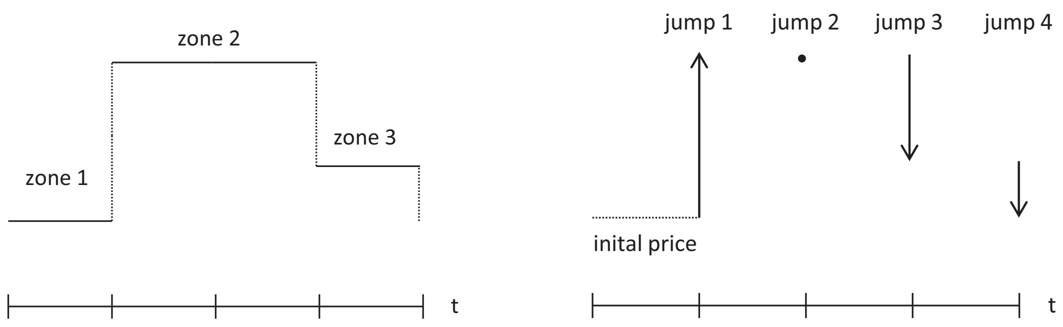
Besides the rate specification itself, the TOU rate design needs to account for optimization objectives and constraints related to the electricity provider, his customers and the regulatory environment. TOU pricing is used to induce load shifting by electricity consumers. The underlying rationales vary and include procurement cost minimization (focus on load balancing), profit maximization (strategic pricing) or minimizing load peaks (grid stability focus). These objectives facilitate the quality assessment of rates and provide a base for optimal design approaches of custom rates. Thus another set of requirements are characterized by,

- modeling and maximization of provider objective,
- customer response and acceptance, as well as
- regulatory restrictions (price limits and rate zone limitations).

5.2 Formal Representation of Time of Use Rates

The first step to building a TOU model is the conceptualization of an abstract representation of such rates. A helpful building block can be identified by realizing that the TOU structure can not only be characterized by rate zones with distinct levels and start times, but also as a collection of price jump decisions over the rate horizon. Then, the presence of a rate jump (non-zero jump magnitude) marks the beginning of a new rate zone. This is illustrated in Figure 5.1.

[2]A very preliminary version of this chapter using an approximate optimization model was presented at the Multikonferenz Informatik 2012 (Ighli et al., 2012).



(a) Rate zone structure **(b)** Rate jump structure

Figure 5.1: Equivalent representations of a time-of-use rate

To describe this TOU rate with three rate zones ($Z = 3$), one can either specify the three price levels and three zone start times — the start point of the initial zone indicating the end of the terminal zone assuming a daily looped structure for the TOU rate. Alternatively, one can specify the initial level and a jump amount (positive or negative) for each time slot change. The example shows how the latter approach includes redundant information (the zero-magnitude jump at $t = 2$). As we will see, this "over-specification" provides a reliable structure for formulating an optimization model. However, it should be noted that this structure is not directly capable of capturing more subtle semantics of TOU rates, such as price zones defined by a set of prices (e.g., a shoulder-peak-shoulder rate structure).

Within a fully specified rate jump structure, the number of time zones Z is given by

$$\max\{J, 1\},$$

where J is the number of jumps with absolute magnitude exceeding zero. Furthermore, for looped TOU rates it holds that $J \neq 1$. This is because there needs to be at least one additional jump to return to the original level after a first rate jump occurred. This representation provides another helpful insight as it helps to formalize the complexity of deriving a TOU with a specified number of rate zones. Acknowledging the equivalence between rate jumps and rate zone starts, the total number N of possible TOU rate structures with Z rate zones is readily expressed as choosing Z rate beginnings from the set of time slots, that is

$$N = \binom{|\mathcal{T}|}{Z}. \tag{5.1}$$

For very small Z values as well as values close to $|\mathcal{T}|$ the number of possible rate structures is fairly limited (1 for $Z = 0$ and $Z = |\mathcal{T}|$), whereas for Z values around $\frac{|\mathcal{T}|}{2}$ the number of combinations becomes very large (see Figure 5.2 for an illustration for $|\mathcal{T}| = 24$). Given the exponential growth of the factorial, the problem complexity increases drastically when a longer time horizons or more granular time discretizations are considered. While such a more granular temporal resolution may not be relevant for private household customers (complexity, acceptance), it would resonate well with the quarter-hour contracts traded at European Power Exchange (EPEX) and may thus be an interesting option for industrial customers.[3] On the other hand, one can also imagine rate designs spanning more than 24 hours, e.g., a weekly rate. Such rates may attract acceptance by retail customers but a naïve design approach would also suffer from the exponential growth of the underlying solution space.

This poses an interesting challenge to rate design: For efficiency reasons, one wants to avoid rate structures with a small number of rate zones, while for customer acceptance reasons one wants to avoid exceedingly complex rate specifications. At the same time rate specifications with an intermediate number of zones pose a complex design problem. This signifies the importance of an appropriate decision tool to support efficient derivation of custom TOU rates with an intermediate number of rate zones.

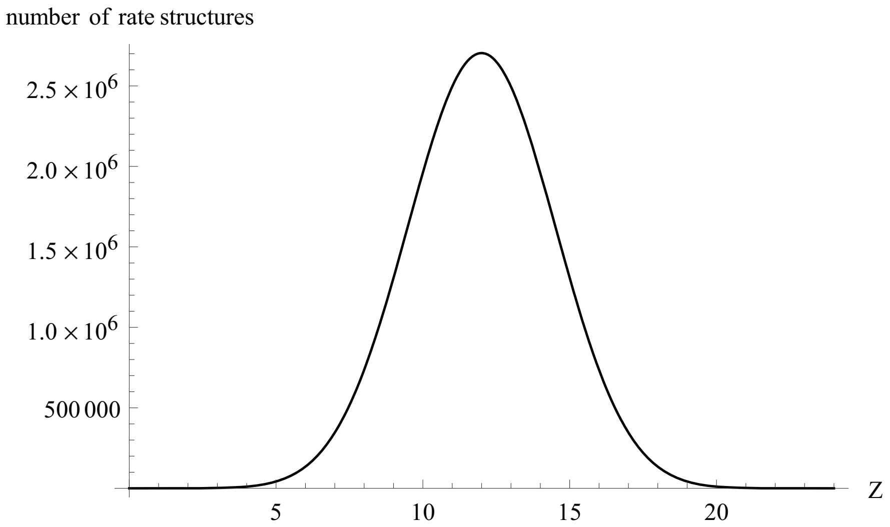


Figure 5.2: Number of TOU rate structures for different values of K ($|\mathcal{T}| = 24$)

5.3 MIP Optimization Model for Time of Use Rates

Previous work on TOU rate design (see, e.g., Oren et al., 1987; Celebi and Fuller, 2007, 2012; Saure et al., 2010) uses exogenous assumptions on the rate structure (i.e. number of rate zones and switching times). Given this rate framework a customized TOU specification obtains as a set of price levels for the exogenous structure. With mild restrictions on the demand functions this optimal price level determination is a convex problem that can be efficiently solved. Such models allow analyzing the efficiency potentials of TOU pricing in certain scenarios but provide no guidance or decision support for suppliers seeking to develop custom rates (e.g., for marketing or hedging purposes). For example, Reiss and White (2005) empirically derive a demand function for electricity and subsequently test the effect of introducing a specific TOU rate with five zones. However, they do not consider alternative specifications of this rate. Ahlert and van Dinther (2009) propose another simple approach

[3] `www.epexspot.com/en/press-media/press/details/press/Fifteen-Minute_Contracts_Successfully_Launched_on_German_Intraday_Market`

for determining TOU rates based on symmetric zoning where all rate zones are of equal length. Given this exogenous rate structure (i.e. symmetric zoning), the optimal rate are then obtained by optimizing each zone independently. Given an hourly jump structure, this allows deriving rates with 2, 3, 4, 6, 8 or 12 zones.[4]

I follow an alternative approach and present a unified optimization model that allows for joint, endogenous derivation of rate structure and price levels building using a MIP. The described artifact is generic in that it can readily be used to reflect alternative optimization objectives as well as incorporate additional or modified constraints. Using an industry-grade optimization suite[5] facilitates integration into data management systems which allows embedding the optimized decisions into near-real-time decision-making. This allows increasing the update frequency of TOU rates which addresses the major drawback of these rates pointed out by Bohn (1982). My MIP approach determines an optimal (with respect to a given objective) and valid (exhibiting a given number of rate zones) TOU rate structure. I develop the problem by first establishing the relevant decision variables as well as a set of constraints to encapsulate the rate structure and ensure rate validity. Subsequently, I turn to the optimization objectives and formulate instances of the optimization problem that can be solved efficiently.

5.3.1 Decision Variables

As noted before, one can structure TOU rates as a collection of rate jump decisions over the time horizon $\mathcal{T} = \{1,...t,...T\}$. For each time slot $t \in \mathcal{T}$ there is a positive real decision variable $p_t \in \mathbb{R}_0^+$, indicating the corresponding price level in t.[6] To acknowledge the presence of rate jumps, I define two binary decision variable vectors $j_t^+ \in \{0,1\}$ and $j_t^- \in \{0,1\}$ indicating whether or not there is a positive (negative) rate jump in t as well as two positive real decision variables $\Delta_t^+ \in \mathbb{R}_0^+$ and $\Delta_t^- \in \mathbb{R}_0^+$ which determine the magnitude of the positive (negative) rate jump in t. Table 5.1 provides an overview of the decision variables.

Table 5.1: Overview of decision variables

Variable	Domain	Description
p_t	$\mathbb{R}_0^+$	Price level at time t
j_t^+	$\{0,1\}$	Occurrence of positive rate jump at time t
j_t^-	$\{0,1\}$	Occurrence of negative rate jump at time t
Δ_t^+	$\mathbb{R}_0^+$	Positive rate jump magnitude at time t
Δ_t^-	$\mathbb{R}_0^+$	Negative rate jump magnitude at time t

Clearly, this is not a minimal (mutually exclusive) set of decision variables as most variables are inter-related. Yet, this expressiveness allows an easier formulation of constraints ensuring internal validity.

[4]Zones with non-integer length seem implausible and would yield limited customer acceptance.

[5]IBM ILOG OPL Studio with the CPLEX solver.

[6]Without loss of generality I restrict this discussion to non-negative price levels.

5.3.2 Constraints

To ensure a valid rate specification, the above set of decision variables requires a corresponding set of constraints:

- *Price level constraint* — The price level specified through p_t must be consistent with the price level p_{t-1} plus the rate jump in t:

$$p_t = p_{t-1} + \Delta_t^+ - \Delta_t^- \quad \forall t \in \{2, ...T\} \tag{5.2}$$

- *Looping condition* — The price level p_1 must be consistent with the price level p_T plus the rate jump in $t = 1$:[7]

$$p_1 = p_T + \Delta_1^+ - \Delta_1^- \tag{5.3}$$

- *Jump consistency constraint* — Price jump magnitude in t is zero if there is no rate jump in t:

$$\Delta_t^+ \leq j_t^+ \cdot \xi \quad \forall t \in \{1, ...T\} \tag{5.4a}$$

$$\Delta_t^- \leq j_t^- \cdot \xi \quad \forall t \in \{1, ...T\}, \tag{5.4b}$$

  where ξ is a sufficiently large positive number.

- *Unique Jumps* — In any given time slot t, there cannot be both a positive and a negative rate jump:[8]

$$j_t^+ + j_t^- \leq 1 \quad \forall t \in \{1, ...T\} \tag{5.5}$$

Besides these constraints governing internal validity of the rate structure, one also needs to account for external rate restrictions. As mentioned before, the limitation on price zones, that is $Z < |\mathcal{T}|$, renders segment-specific TOU rate design a complex task compared to a RTP regime where $Z = |\mathcal{T}|$. One thus needs to incorporate a *rate zone limit* constraint, that is the total number of rate jumps cannot exceed rate zone limit Z:

$$\sum_{t=1}^{T} (j_t^+ + j_t^-) \leq Z \tag{5.6}$$

One could also imagine a setting where Z is not provided as an exogenous constraints, but rather endogenized in the form of goodwill/ administrative costs of increasing rate complexity. Z would the be an additional decision variable with an appropriate "cost" term in the objective function.[9] In the following, I focus on the case of an exogenously specified Z value.

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[7] Note that I label the price jump occurring after T with 1.

[8] Given the typically binding nature of constraint (5.6), this constraint is not necessary for problem validity but provides the solver with additional cutting planes.

[9] For a discussion of a related problem with complexity costs of product diversification, see Knapper et al. (2011).

Additional Constraints

Moreover, depending on the regulatory regime, operators may be faced with price ceilings requiring period price levels to remain below certain levels, average cost limitations restricting total costs borne by customers, minimum zone length requirements or limitations on the magnitude of rate jumps. Further constraints need to be introduced to properly account for such additional design limitations on rate design. The rate model as formalized above facilitates the easy creation of these additional constraints. For example, a minimum zone length requirement of two time slots can be enforced by modifying Equation (5.5) in the following manner:[10]

$$j_t^+ + j_t^- + j_{t+1}^+ + j_{t+1}^- \leq 1 \quad \forall t \in \{1, ...T-1\} \tag{5.7}$$

Again modeling rate zones as a series of jumps provides an expressive way to describe fairly complex rate rules: One can limit the number of rate jumps in two subsequent time slots to one. This translates to a rate zone length of at least two time slots.

Similarly, one can implement rates with symmetric zoning by requiring jumps to occur at boundaries of the symmetric zones (the set of boundaries is denoted by B):

$$j_b^+ + j_b^- \geq 1 \quad \forall b \in B \tag{5.8}$$

These additional constraints illustrate the design power embedded in the MIP framework for TOU rate design.

5.3.3 Objective Functions

The answer to the question “what is a good rate” ultimately boils down to the objective function applied for the rate determination. Candidate functions need to retain the problem's feasibility (linear or semi-definite quadratic program) and at the same time need to account for possible reactions to rate specification. In certain cases, the latter may require the introduction of further constraints to ensure problem and rate validity. Focusing on the establishment of a functional framework for the design of customized TOU rates, I illustrate only exemplary objective functions in the following — procurement cost matching and supplier profit maximization. Alternative coordination goals, e.g., peak load reduction or demand smoothing can be achieved by using appropriately adjusted optimization problems. Furthermore, I restrict my attention to stylized demand functions and do not address alternative demand modeling approaches.[11] Furthermore, one needs to account for the challenges arising when considering own-price and cross-price elasticity of demand.

[10] An additional constraint is required to ensure the rate zone length from $t = T$ to $t = 1$.

[11] This is in line with the goal of obtaining a top-down characterization of responsive household load in Chapter 4.

5.3.4 Procurement Cost Matching

A straight-forward objective for TOU rate design is optimizing the match between procurement cost and retail price of electricity — i.e. minimizing the deviation between the two. This objective corresponds to the task of an electricity broker aiming to minimize risk when buying and selling electricity. In this setting, the energy provider tries to couple retail customers to the wholesale electricity in the spirit of Faruqui et al. (2010). Thus the energy provider is not acting strategically in the sense of setting profit-maximizing prices but rather acts as a market maker minimally interfering with customer-market interaction.[12]

The main building block for this objective function is the collection of hourly spreads between retail price p_t and procurement costs c_t, $p_t - c_t$. Depending on the concrete scenario (hedging cost structure, supplier risk evaluation), one can either minimize the sum of absolute spreads[13],

$$\min_{p_t, j_t^+, j_t^-, \Delta_t^+, \Delta_t^-} \sum_{t=1}^{T} |p_t - c_t|, \tag{5.9}$$

or the sum of quadratic spreads,

$$\min_{p_t, j_t^+, j_t^-, \Delta_t^+, \Delta_t^-} \sum_{t=1}^{T} (p_t - c_t)^2. \tag{5.10}$$

Note that while the objective function only features the set of price level decision variables p_t, the full program also needs to determine j_t^+, j_t^-, Δ_t^+ and Δ_t^- which ensures rate structure validity in correspondence with the optimization constraints discussed above. The absolute spread formulation implicitly introduces additional integer constraints reflecting the embedded logical structure. The quadratic spread, on the other hand, model yields a quadratic program posing additional constraints on the optimization problem to ensure semi-definiteness. Other functional forms are not readily applicable within the MIP framework.

Besides these alternative weighting approaches for the spread magnitude, electricity brokers may also want to account for the demand level x_t when designing a rate. This is because a rate mismatch is more costly in the case of high trade volumes (i.e. during times of the day with a high demand level). The adjusted objective functions then read as

$$\min_{p_t, j_t^+, j_t^-, \Delta_t^+, \Delta_t^-} \sum_{t=1}^{T} x_t |p_t - c_t|, \tag{5.11}$$

[12]Concerning the vertical relationship between generator, supplier and customer this scenario will not induce double marginalization (Spengler, 1950; Economides and Woroch, 1992) as the supplier will effectively act in a translucent manner.

[13]See Code D.1 in the Appendix for the complete ILOG OPL specification of the optimization problem.

and respectively,

$$\min_{p_t, j_t^+, j_t^-, \Delta^+, \Delta_t^-} \sum_{t=1}^{T} x_t \left(p_t - c_t\right)^2. \tag{5.12}$$

With the availability of customer-specific load profiles (Chapter 4), demand-weighted rate design provides a straight-forward and easily implemented means to determine individualized rates for different customer segments.

An obvious limitation of the latter formulations is the exogenous nature of the demand term x_t. Clearly, customer demand will typically respond to price variations (this is the underlying rationale for monetary DSM approaches, Strbac, 2008). Thus an appropriate formulation will have to endogenize demand effects of price changes using a functional relationship between the demand vector $\mathbf{x}$ and the TOU price vector $\mathbf{p}$, that is $\mathbf{x}(\mathbf{p})$. I look at this problem in more detail in the subsequent section on profit maximization.

5.3.5 Profit Maximization

Fundamentally, time-of-use pricing provides a means for price discrimination as suppliers can extract rents from inflexible consumption (Oren et al., 1987). Abstracting from retail competition[14], this is a case of the multi-product monopolist pricing problem (Tirole, 1990, pp. 69–72) where the "products" are the different consumption periods specified through the TOU rate. When following a profit maximization goal in rate design, one must account for the impact on the demand level to formulate a bounded optimization problem. Otherwise, an energy supplier would optimally drive prices up to infinity. Therefore, one needs to model price elasticity of demand. For a comprehensive overview of applied demand modeling I refer to Talluri and van Ryzin (2004, pp. 311–327). Kirschen (2003) discusses general issues in electricity demand modeling and Espey and Espey (2004) provide a meta-study on the price elasticity measures of electricity demand.

For brevity and exposition, I focus on linear demand functions which is a standard approach in electricity market modeling as reported by Ventosa et al. (2005). Such linear demand models are also an attractive choice given their robust estimation properties (Talluri and van Ryzin, 2004, p. 323). Here, the demand for electricity in period t, x_t is given by

$$x_t(p_t) = (a_t - b_t p_t), \tag{5.13}$$

where the intercept a_t indicates the gross demand potential of the period and the slope b_t encapsulates the price sensitivity of demand. To ensure non-negative demand levels, one needs to include an additional constraint,

$$p_t \leq \frac{a_t}{b_t} \quad \forall t \in \mathcal{T}. \tag{5.14}$$

[14] While this is a strong assumption, the results obtained are indicative for a competitive setting.

Besides the own-price elasticity, one may also consider cross-price elasticity in a TOU context: the price in period i can influence the demand level in another period j (Venkatesan et al., 2012). Talluri and van Ryzin (2004) specify the generalized linear demand function with cross-price elasticity as

$$\mathbf{x}(\mathbf{p}) = \mathbf{a} + \mathbf{B}\mathbf{p}, \tag{5.15}$$

where $\mathbf{x}$ is the demand vector over the different periods, $\mathbf{p}$ is the price vector, $\mathbf{a}$ is the gross demand vector and $\mathbf{B}$ the elasticity matrix. The determination of the elasticity matrix $\mathbf{B}$ is a central obstacle to applying multi-product demand functions in TOU settings as there is so far only very limited data available. However, with increasing penetration of advanced metering infrastructure as well as innovative pricing regimes, more data for elasticity estimation should become available.[15]

Theoretical Benchmark Problem

For a general demand function and a *fixed* rate structure (a given set of products), the optimal prices are characterized by the following condition (Tirole, 1990, p. 70):

$$\frac{p_i - c_i}{p_i} \equiv \frac{1}{\epsilon_{ii}} - \sum_{j \in \mathcal{T} \setminus i} \frac{(p_j - c_j) x_j \epsilon_{ij}}{R_i \epsilon_{ii}} \quad \forall i \in \mathcal{T}, \tag{5.16}$$

where

$$\epsilon_{ii} = -\frac{\partial x_i}{\partial p_i} \frac{p_i}{x_i}$$

is the own-price elasticity of electricity demand in time slot i, and

$$\epsilon_{ij} = -\frac{\partial x_j}{\partial p_i} \frac{p_i}{x_j}$$

is the cross-price elasticity of demand for electricity consumption in time slot j with respect to the price of electricity in time slot i. For the case of substitute products – a typical assumption when considering electrical load shifting – the monopolist optimally adjusts period prices upwards to account for the implicit "competition" between time slots.

While this is an elegant and generic approach to determine the profit-maximizing RTP levels or fixed TOU rate structures, it cannot be applied when rate structure and price levels are being derived simultaneously.

Profit Maximization within the MIP Implementation

The linear optimization program specified above becomes quadratic when optimizing firm profit under the simple (no cross-substitution) linear demand function

[15] See Taylor et al. (2005) for an extensive analysis of industrial cross-elasticities.

(5.13). The objective function of the rate design problem is then given by

$$\max_{p_t, j_t^+, j_t^-, \Delta_t^+, \Delta_t^-} \sum_{t=1}^{T} x_t(p_t)(p_t - c_t). \tag{5.17}$$

Running the above problem specification yields a profit-maximizing TOU rate specification. This demand specification can also be applied to the cost-price spread minimization objective discussed before.

One can identify two limitations of the optimization program which are the reliance on the linear demand model and the absence of cross-product substitution effects. The former limitation arises from restrictions on the functional form within MIP optimization which can only handle linear or quadratic objective functions. However, linear approximations provide a work-around for this problem (see Ahlert, 2010). The application of the full demand functions with cross-product effects (5.15) is problematic for another reason: Let the price p_j in period j (a decision variable of the TOU design problem) influence demand x_i in period i, that is $x_i(p_j, ...)$. Then, the profit objective will contain the term $p_i x_i(p_j)$ and thus feature a multiplicative relationship between two decision variables, p_i and p_j. Such problems cannot be solved in the chosen MIP framework as products of decision variables violate the underlying linear programming requirement. In the following, I sketch an iterative approximation to include cross-product substitution.

Iterative Approximation of Substitution Effects

Recognizing that one cannot account for cross-product substitution during the optimization, one can tackle the rate design problem iteratively: One first initializes the problem as described above and obtain a myopically optimal rate design only accounting for own-price elasticity. Then, the cross-substitution effects which are induced by this rate and increase the gross demand (single product demand without other products) for all time slots by these substitution amounts are determined. The optimization problem is run again with the modified demand intercepts.[16] One repeats this procedure iteratively until the profit expression converges. While this procedure does not warrant optimality of the rate obtained, my results indicate that it can substantially increase the efficiency of the rate design.

5.4 Evaluation

This section serves to illustrate the results from customized TOU rate design. I want to primarily analyze the rates obtained under different number of rate zones and compare these with rates obtained with symmetric zoning. I describe the energy broker scenario considered as well as the system setup used to run this analysis. Finally, I perform both visual and statistical analysis on the results.

[16] To improve continuity of the approximation scheme I use a linear combination of the substitution demand from the current and previous price vectors.

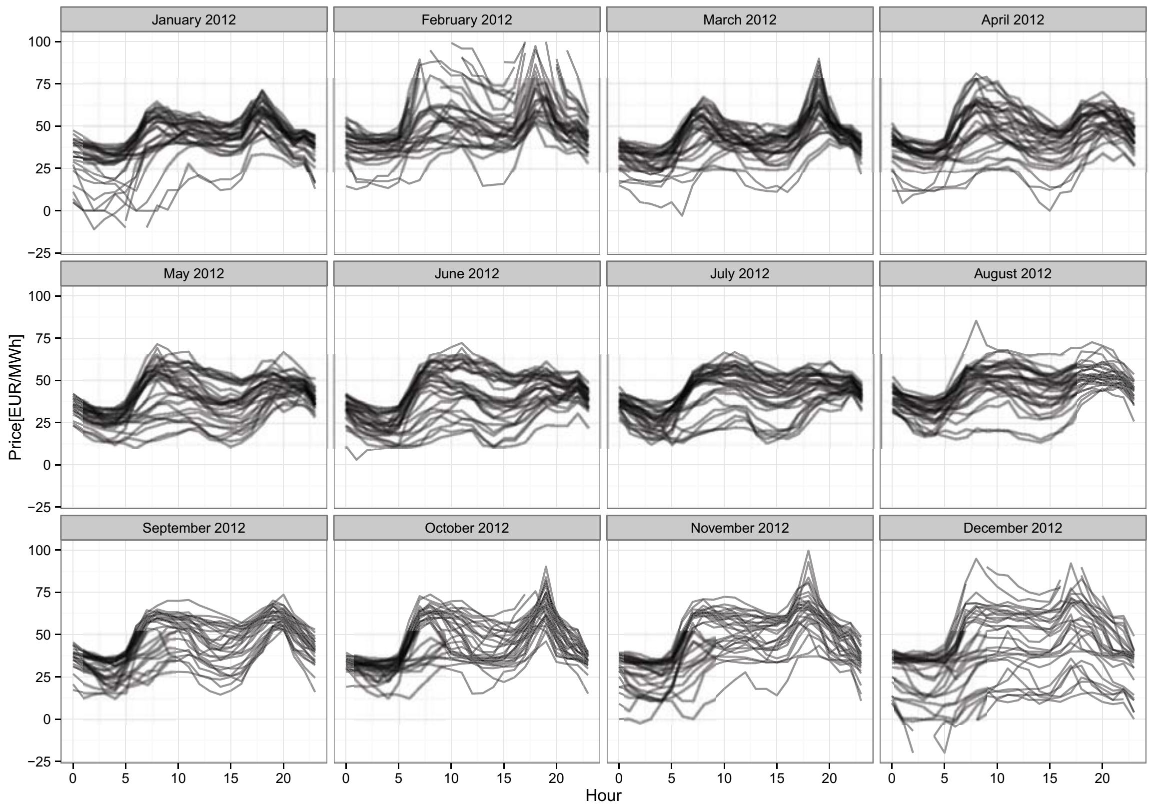


Figure 5.3: Daily EPEX price curves in 2012 (incomplete curves are due to values above 100 EUR/MWh or below -20 EUR/MWh

5.4.1 Scenario

For sake of exposition, I focus on a scenario with hourly price adjustments and a rate time horizon of one day, i.e. a maximum of 24 possible rate zones.[17] Abstracting from demand side response, the procurement cost matching objective is especially helpful for illustrating the efficiency potentials of customized TOU rate design as it requires a very limited set of assumptions on costs (price scenarios) and the specific objective function (absolute versus quadratic deviation). On the other hand, a setting incorporating demand reactions will require a large number of assumption concerning the functional specification of demand. To avoid the additional bias arising from these assumptions, I restrict my analysis to the cost-matching objective. Specifically, I consider the case of an electricity broker with procurement costs based on German EPEX spot prices from 2012. As shown in Figure 5.3, these prices exhibit significant volatility. I look at the structure of the rates obtained for different values of Z over different optimization horizons and considering alternative objective functions. Furthermore, I quantify the efficiency gains that can be achieved by increasing the number of rate zones. To account for the effect of aggregation biases and to quantify the potential of updated TOU rates, I look at different price scenarios with different rate design horizons.

[17] It should be noted that the MIP scales fairly efficiently in the number of time zones for problems with linear objective functions. Experiments indicate that even for $Z = 336$ a solution is found within approximately 10 seconds for linear objective functions. However, for quadratic objective functions the solution speed is significantly worse.

5.4.2 Workflow and System Design

To be able to efficiently derive and evaluate custom TOU rates in a variety of scenarios I use an integrated approach using JAVA for data handling (import and export) and problem modeling, IBM ILOG for optimization tasks and GNU R for visualization and statistical analyses. This setup can be considered a pilot setup for a rate design Decision Support System (DSS). In a professional setting these tools would additionally have to be linked with other corporate systems such as ERP or CRM.

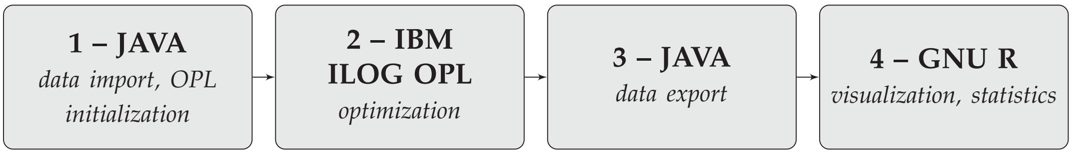


Figure 5.4: Integrated System for Custom Rate Design

5.5 Rate Structures

The goal is to optimally determine both the rate structure and the price level of custom TOU rates. The most basic evaluation is thus a visual analysis of the rate structures obtained in different scenarios. On the one hand, this allows a simple verification of the optimization program functionality, on the other hand it facilitates a high-level identification of typical structural patterns within customized rates.

5.5.1 Rate Granularity

I have argued, that the central design feature of a TOU rate is the number of rate zones Z. Figure 5.5 illustrates for a single day the optimal rate structure for $Z \in \{1,..24\}$. One can directly see the importance of endogenously determining the length and position of the rate zone. For $Z = 2$, the lower price night rate is distinctly shorter than the day rate zone. Similarly, additional time zones are often used to shape a specific rate feature. This indicates, a symmetric zoning approach for determining TOU rates as used by Ahlert and van Dinther (2009) is not optimal and will yield a less efficient TOU rate structure for a given number of rate zones. Figure 5.6 illustrates the comparison of optimal rate designs with symmetric zones and asymmetric zones for $Z \in \{2,3,4,6,8,12\}$. Especially for $Z = 2$ and $Z = 3$, the zone symmetry requirement yields very different rate designs than the optimal unconstrained rate: For $Z = 2$ one effectively ends up with a single zone and for $Z = 3$ there are only two zones. In both cases, zone symmetry effectively defeats the potential of an additional rate zone. Therefore, symmetric rate zones not only limit the set of possible zone numbers, it also yields suboptimal usage of a given number of zones.

Interestingly, the rate structures obtained for $Z = 4,5,6$ exhibit distinct shoulder-peak-shoulder characteristics with the price level before and after the 15.00-19.00 peak being almost identical. Considering the discussion on rate zones versus price

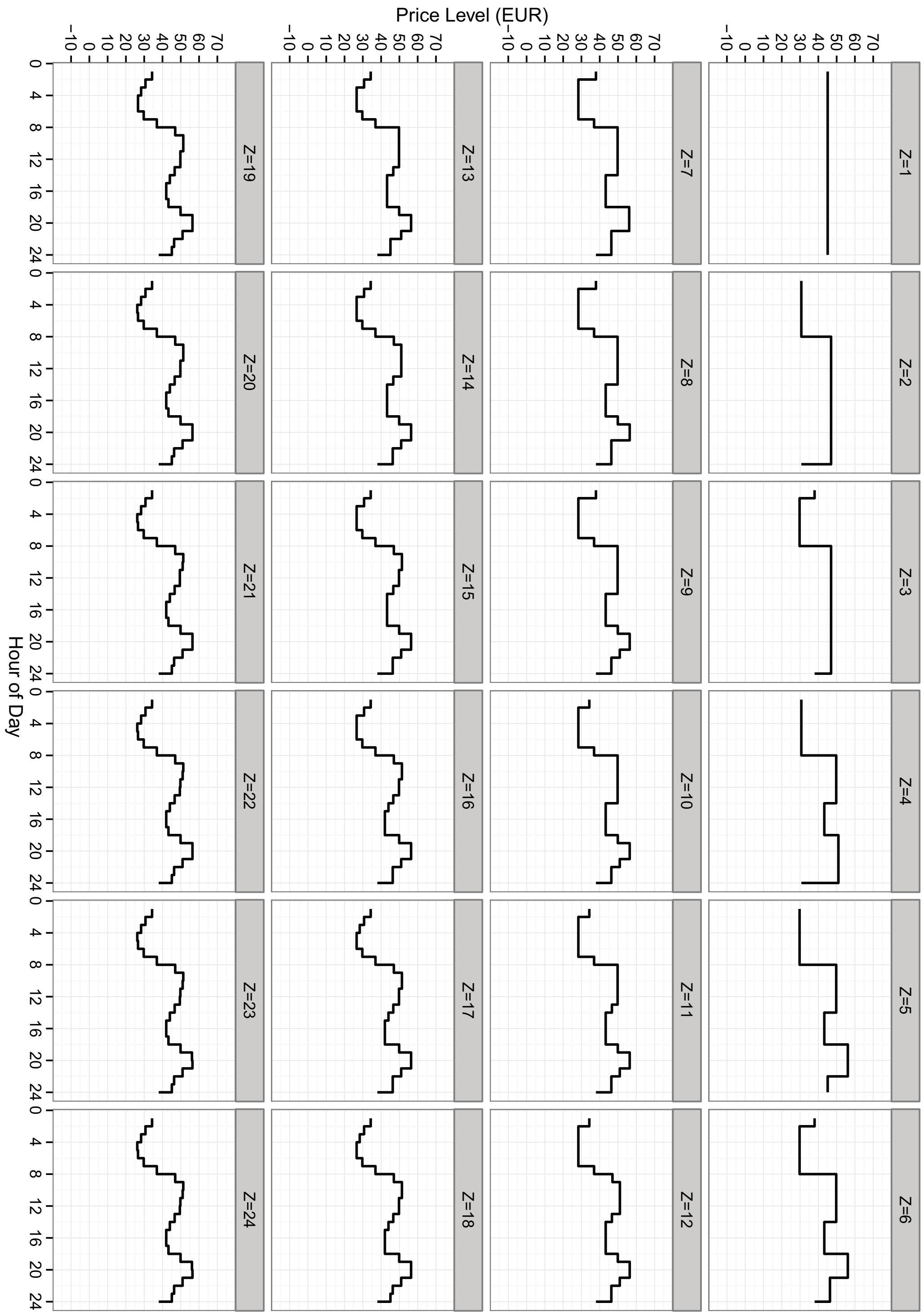


Figure 5.5: Evolution of optimal rate structures for procurement cost matching for increasing Z (Annual rate updating, absolute error weighting)

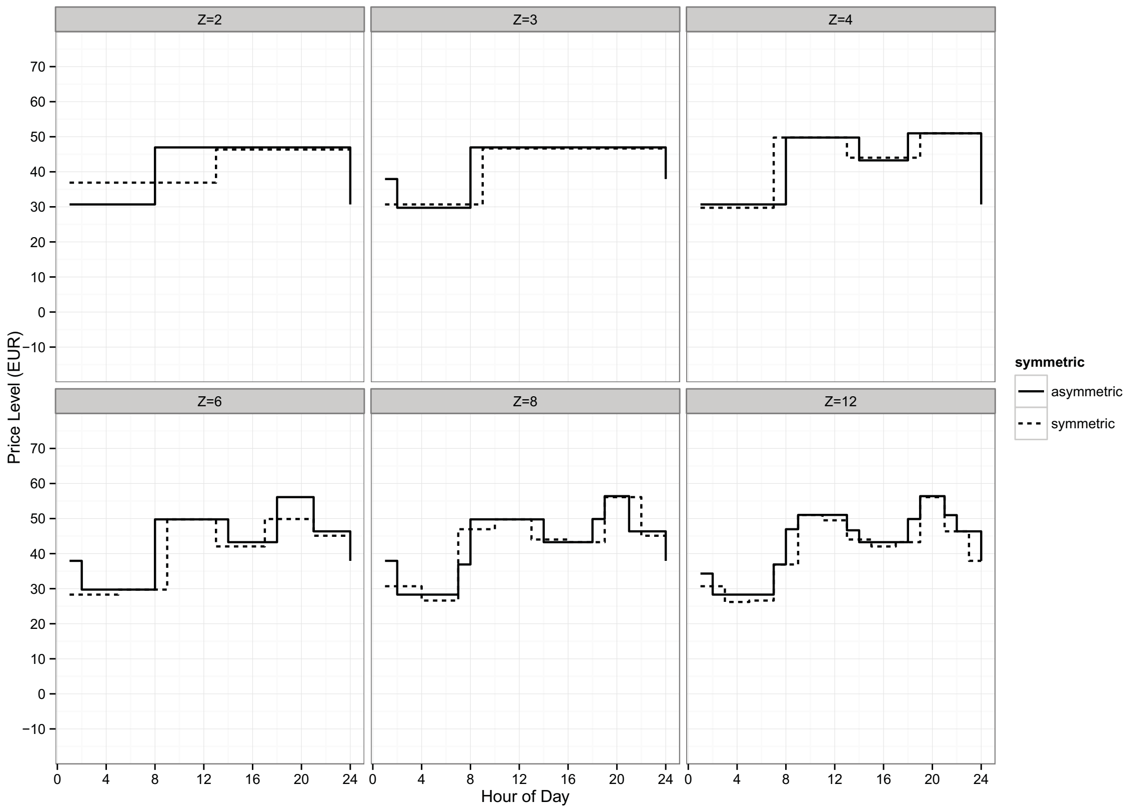


Figure 5.6: Comparison of annual rates with symmetric and asymmetric zoning

zones in Section 5.2, this observation confirms the slight discrepancy between price and rate zone-based formalization of TOU rates.

5.5.2 Rate Updating Frequency

The TOU critique by Bohn (1982) centers mainly around the static nature of these rates. However, with the availability of smart grid ICT infrastructure, more frequent rate updates can be imagined. For an initial assessment of the potential of such dynamic TOU rates, it is illustrative to consider the varying rate structures obtained under different updating schemes.

For the rate structures depicted in Figure 5.7 I consider annual, quarterly, monthly, weekly and daily rate updates for a selected number of rate granularity levels with $Z \in \{1,2,3,6,12\}$. Here, the annual column shows the single optimal rate design that minimizes cost deviation based on the average hourly EPEX prices in 2012. Similarly, the second column shows the four optimal rate designs for each quarter and the third column the twelve rates for each month. To avoid visual overload, the last two columns only feature a selection of the possible 52 respectively 366 optimized rate structures obtained under weekly and daily updating. The rate structures obtained for alternative objective functions (minimization of quadratic and demand-weighted deviation) can be found in the Appendix (Figures D.1 and D.2). As the differences are not too pronounced, I focus on minimizing the absolute deviation in the remainder.

The heterogeneity of rate structures in scenarios with more frequent updating indicates the potential efficiency gains offered by dynamic TOU rates. Besides this obvious relationship, a more subtle observation can be made when considering combinations of rate granularity level and updating frequency: For low updating frequencies (annual to monthly), one can see only limited differences between the rate structures for Z values greater one, whereas for weekly and daily updates there is much greater variety in rate structure shapes, especially for $Z = 6$ and $Z = 12$. This hints towards the possibility, that theoretic efficiency gains of more granular rates may note be achieved with infrequent rate updates.

5.6 Rate Efficiency

Having established the functionality of the customized TOU rate design approach, I am interested in evaluating the efficiency level achieved with respect to rate granularity and update frequency. Owing to my broker scenario (and the optimization objective), my rate efficiency measure is the average hourly matching error between spot and retail price in a given scenario. Besides rate granularity and update frequency, I additionally look at separating weekdays and weekend days to reduce price variance. This is analogue to the clustering scenarios used in Chapter 4. For my analysis, the rates are optimized based on the average hourly spot price over all corresponding scenario hours. Clearly, one cannot evaluate the efficiency using the average prices but rather needs to consider concrete realizations. Efficiency is thus determined by summing the absolute deviation between all scenario hours and the corresponding rate levels.

5.6.1 Descriptive Analysis

The results of the efficiency analysis are summarized in Figure 5.8. The top panel illustrates the differences between symmetric and asymmetric TOU rate designs for $Z \in \{1,2,3,6,12\}$. One can see a fairly large efficiency improvement when going from one to two price levels. As expected, symmetric zoning mostly performs worse than asymmetric zone structures. These differences are less pronounced for more granular rates. Interestingly, symmetric rate designs exhibit distinct non-monotonicities of efficiency in the number of rate zones. This is an important result which requires us to choose the number of rate zones for TOU rates with symmetric zones more carefully.

To be able to visually interpret further efficiency potentials, I remove $Z = 1$ from the lower panel and extend the range of rate zones $Z = 24$. The analysis shows that providing distinct weekend and workday rates improves the cost matching ability of optimally chosen TOU rates.[18] Similarly, rate efficiency is increasing for higher update frequencies. The efficiency gain from increasing the updating frequency is fairly gradual when moving from annual to weekly updating. Roughly speaking, an increase in update frequency by one level improves efficiency by a similar amount

[18] Clearly, for daily updating this argument is not applicable as each day is already provided with a distinct rate design.

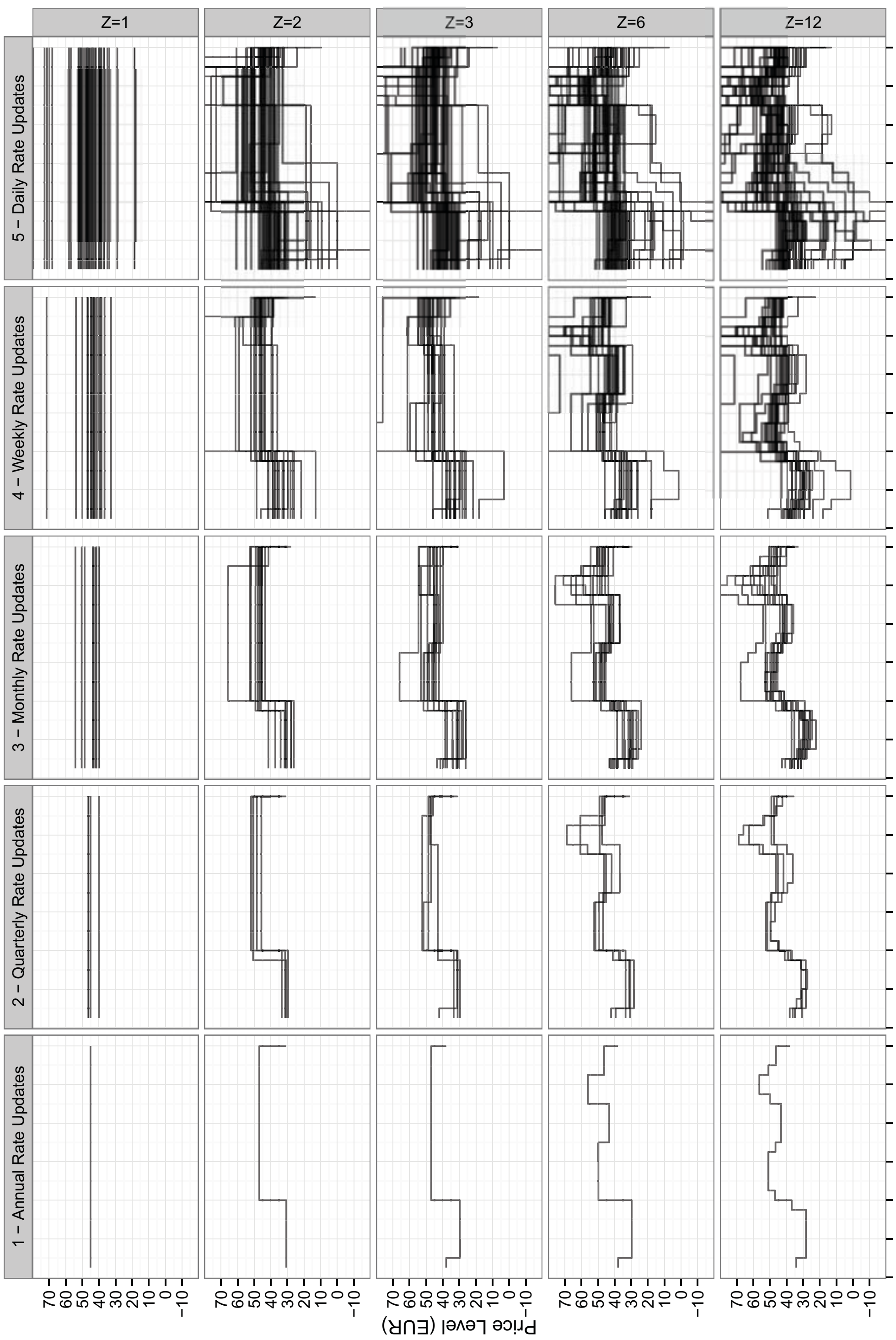


Figure 5.7: Optimal rate structures for procurement cost matching under different updating frequencies for selected Z values (absolute error weighting, only selected rates are depicted for weekly and daily updates)

as increasing rate granularity from $Z = 2$ to $Z = 24$ does. Additionally, one can see that without daily updating efficiency gains from higher rate granularity very much stagnate around $Z = 8$.

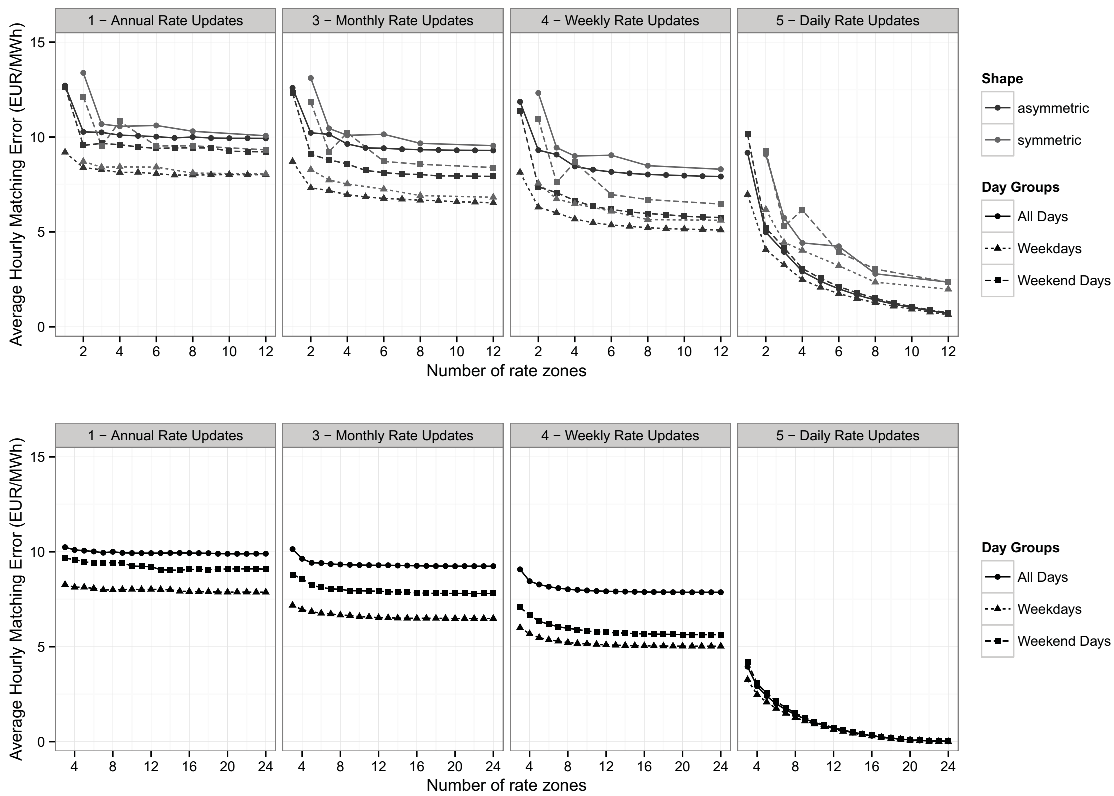


Figure 5.8: Efficiency of different rate granularity levels and rate zone symmetry constraints (absolute weighting of errors, upper panel: $Z \in \{1,2,3,6,12\}$, lower panel: $Z \in \{2..24\}$)

As the rates are derived from the average price curve over the updating interval it should be noted that there is no strict efficiency gain from a greater number of rate zones except for daily updating where this forecast error vanishes. Under this regime the average matching error is strictly declining in the number of rate zones with the average matching error reaching zero for $Z = 24$. However, already for $Z = 12$ one obtains hourly matching errors below 1 €/MWh. These results are obtained under perfect foresight and thus need to be interpreted accordingly.

Another particularly striking observation is the behavior of the efficiency curve for symmetric rates on the weekend. Here, efficiency drops significantly from three to fours rate zones. This is because the even spacing of three rate zones is better aligned with the optimal asymmetric rate zone than the even spacing of four rate zones. This is illustrated in Figure 5.9.

In summary, these observations suggest that efficient usage of TOU rates needs to jointly account for rate granularity and update frequency — for infrequent rate updates a two zone rate is sufficient while for daily rate updates twelve or more zones should be considered. Furthermore, the results suggest that symmetric time zone requirements have a detrimental effect on rate efficiency.

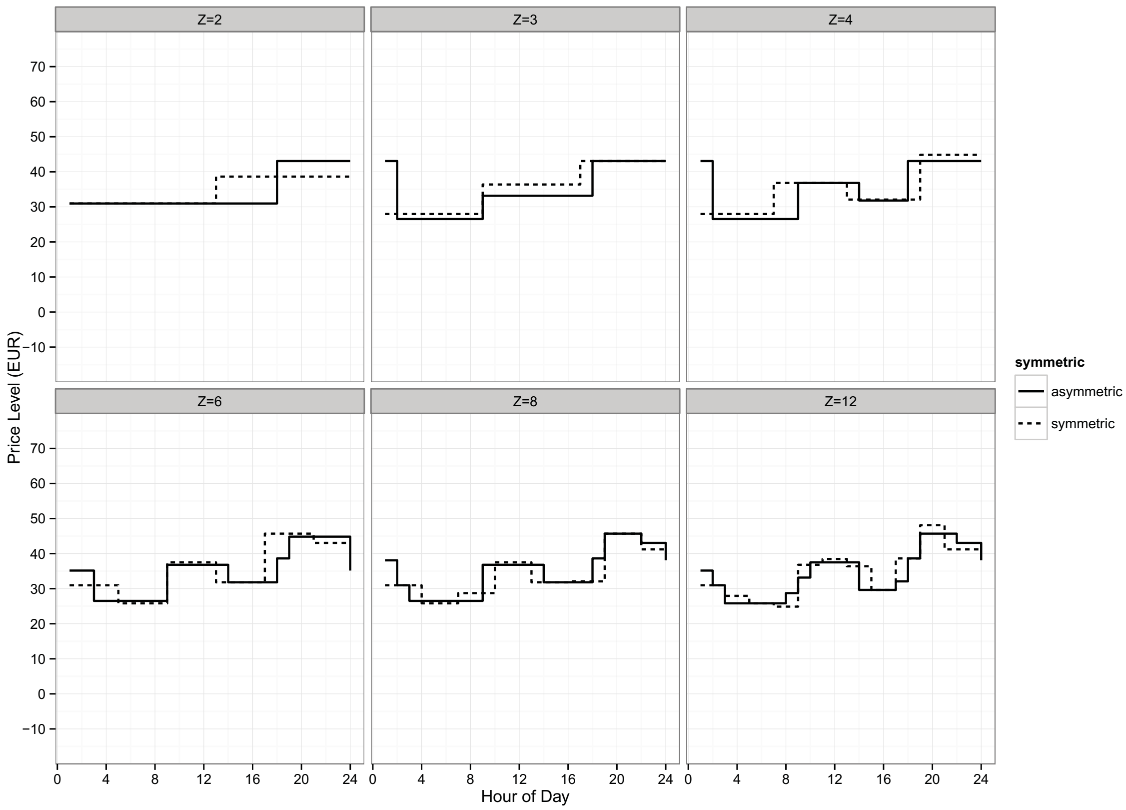


Figure 5.9: Comparison of annual rates with symmetric and asymmetric zoning for weekend days

5.6.2 Regression Analysis

I want to complement the qualitative results by estimating the parameters of a linear regression model in order to explain the matching errors. Considering the insights obtained from Figure 5.8, I restrict the analysis to the data set without single zone rates. Similarly, I condense the day groups into a single dummy variable representing either pooled or differentiated day types (i.e. workdays and weekend days separated). This yields the following set of independent variables: *Number of rate zones* and dummy variables indicating the presence of *Quarterly Rate Updates*, *Monthly Rate Updates*, *Weekly Rate Updates*, *Daily Rate Updates*, *Symmetric Zoning Requirement* and *Differentiated Day Types*.

All independent variables obtain as significant in reducing the matching error (Table 5.2) and one achieves a high level of explained variance with an adjusted R^2 of 0.489. Each additional time zones reduces the hourly matching error by 0.2 which indicates the value of more granular electricity pricing. Introducing more frequent updating also greatly reduces the hourly matching error — by 1.277 Euro for quarterly, 1.646 Euro for monthly, 2.473 Euro for weekly and 7.347 Euro for daily rate updates. Similarly, the introduction of differentiated day types reduces the matching error by 0.460 Euro. Requiring symmetric zone lengths increases the hourly matching error by 1.406 Euro.

The first regression model specification does not allow an interpretation concerning the interplay between rate updating and rate granularity. However, the analysis of Figure 5.8 suggests this interconnection. To quantitatively address this question,

Table 5.2: OLS regression for matching errors

	Dependent variable:
	hourly matching error
	OLS
Number of rate zones	-0.200^{***}
	(0.003)
Quarterly Rate Updates	-1.277^{***}
	(0.326)
Monthly Rate Updates	-1.646^{***}
	(0.303)
Weekly Rate Updates	-2.473^{***}
	(0.295)
Daily Rate Updates	-7.347^{***}
	(0.292)
Differentiated Day Types	-0.460^{***}
	(0.033)
Symmetric Zoning Requirement	1.406^{***}
	(0.045)
Constant	11.329^{***}
	(0.294)
Observations	28,158
Adjusted R^2	0.489
Residual Std. Error	$2.768 (df = 28150)$
F statistic	$3,853.183^{***} (df = 7; 28150)$
Note:	$^{*}p < 0.1; ^{**}p < 0.05; ^{***}p < 0.01$

I specify a second regression model featuring additional interaction terms between the number of time zones and the various updating frequencies.[19]

While this richer model only has a slightly higher adjusted R^2 of 0.506, it sheds light onto the mechanics of the matching error with the results confirming my initial hypotheses concerning the interplay between updating frequency and rate granularity: The number of rate zones is no longer a significant variable. The explanation for this changed result lies in the interaction term between daily updating and the number of rate zones which obtains highly significant with a coefficient value of -0.222. Therefore, the rate at which rate granularity can contribute to reducing the matching error critically hinges on the updating scheme. In the same vein, the efficiency impact of daily updates is less pronounced in the second regression (-5.090 vs. -7.347) — moving to daily updating of rates is thus most effective when combined with a more granular rate structure. The other observations concerning other updating frequency levels, the differentiation of day types and symmetric the zoning requirement remain valid in the richer model.

[19]Note that the number of rate zones are encoded as 0-23. This choice avoids a distorted parameter estimate for the updating variables arising from the presence interaction effects.

Table 5.3: OLS regression for matching errors (model with interaction terms)

	Dependent variable:
	matching error
	OLS
Number of rate zones	-0.018
	(0.042)
Quarterly Rate Updates	-1.114^{*}
	(0.570)
Monthly Rate Updates	-1.160^{**}
	(0.531)
Weekly Rate Updates	-1.991^{***}
	(0.515)
Daily Rate Updates	-5.090^{***}
	(0.511)
Differentiated Day Types	-0.460^{***}
	(0.033)
Symmetric Zoning Requirement	1.408^{***}
	(0.044)
Number of rate zones:Quarterly Updates	-0.016
	(0.046)
Number of rate zones:Monthly Updates	-0.047
	(0.043)
Number of rate zones:Weekly Updates	-0.047
	(0.042)
Number of rate zones:Daily Updates	-0.222^{***}
	(0.042)
Constant	9.469^{***}
	(0.511)
Observations	28,158
Adjusted R^2	0.506
Residual Std. Error	$2.721 (df = 28146)$
F statistic	$2{,}627.036^{***} (df = 11; 28146)$
Note:	$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

5.7 Discussion

As intuited, well-specified rates can achieve very high efficiency levels. Therefore, customized TOU rates can help mitigate the misalignment between customer acceptance and load coordination goals as one can determine rates with limited complexity (i.e. rates with an intermediate number of time zones) and still ensure high efficiency. Energy suppliers have three main levers to improve rate efficiency with respect to representing procurement costs — rate granularity, rate update frequency and differentiation of day types.

The analysis shows that the most effective first step for achieving better cost representation through retail electricity prices is establishing well-designed (i.e. non-symmetric) TOU rates with two zones. Subsequently, an increase of the update frequency of the rate allows to further improve rate efficiency. Similarly, differentiating rate designs on a day type base allows to reduce the cost matching error. Additional rate zones beyond two yield only limited efficiency increases if rates are not updated on a daily basis. However, in a daily updating regime higher rate granularity levels help achieve much higher efficiency. I also show that it is detrimental to the efficiency of TOU rates to require symmetric rate zone lengths.

5.7.1 Limitations

Within the evaluation, rate design was based on hourly means obtained under perfect foresight. While the subsequent efficiency assessment uses individual scenarios and is thus able to analyze the effect of the different rate design aspects, the effect of uncertainty with respect to the hourly means remains unclear as illustrated by the zero forecast error for the daily updating regime with 24 zone rates. Potentially, the presence of uncertainty improves the relative efficiency of less granular rate designs due to higher robustness. Price backcasting as discussed in Chapter 6, random distortion (Ahlert, 2010) or price processes (Möst and Keles, 2010) can be applied to incorporate price uncertainty in rate design.

I have focused on the cost-matching objective to avoid arbitrary demand specifications. However, my evaluation is based on the implicit assumption that the energy supplier procures all energy on the spot market. This ignores the availability of futures and forwards markets which are typically leveraged for sake of risk management. Concerning the practical relevance, the current regulatory regime in Germany does not yet facilitate a roll-out of time-variable nor dynamic electricity pricing. Consequently, the results are not directly applicable in a business context and depending on new market rules may likely need to be adapted appropriately.

5.7.2 Future Opportunities

My analysis currently only considers rate updates specifying a complete rate structure. However, one alternative could be to issue partial rate updates that transform the previous rate in a simple manner, e.g., by shifting all price levels up with other rate elements remaining unchanged. Such limited price updates could potentially reduce rate (and communication) complexity and thus assist in increasing customer acceptance. It would be interesting to see, how much welfare is lost through constrained updating and how it interacts with other rate design elements. Similarly, it may be worthwhile to investigate the efficiency impact of other rate design constraints such as minimum zone length, price jump limits or limiting the number of distinct price levels. The effect of uncertainty is especially interesting in the context of rates with longer horizon, spanning, e.g., a whole week instead of a single day.

As noted above, the interconnection between demand modeling — determining price elasticity as well as demand functions — and rate design is of special interest, especially when determining rates with a profit maximization objective. Consequently, the rate design approach can be applied in conjunction with richer demand models. Similarly, future research can also investigate the customer side with respect to behavioral dimensions such as the acceptance and response to alternative TOU specifications. The analyses by Goett et al. (2000) and Gerpott and Paukert (2013) offer first insights into customer acceptance and choice of rates.

Part III

Modeling and Coordinating Electric Vehicle Loads

Chapter 6

Electric Vehicle Models

Large-scale charging of EVs will constitute both a large (the energy required for an annual driving distance of 18,000 km roughly equals average annual household electric energy consumption in Germany) and flexible load (ICT-enabled systems can realize charging at any time of the day). Furthermore, EVs have limited range which requires frequent recharging as well as adapting new mobility expectations and requirements. Consequently, the analysis of the effects of a large-scale EV roll-out has attracted researchers from diverse disciplines — e.g., electrical engineering, economics as well as information systems. These research contributions (e.g., Lopes et al., 2009; Sioshansi, 2012; Goebel, 2013) aim to characterize the mobility potentials of EVs and estimate the resulting charging loads as well as to identify options for efficient charging coordination aligning mobility requirements and charging activity. Appropriate EV customer models constitute the base for such analysis. Given their central importance I want to revisit EV customer modeling in light of the framework from Chapter 3.[1]

I first derive the EV model primitives — technical vehicle specifications as well as general driving behavior — from empirical data. The required charging energy of a given EV model can be described through these basic properties. This establishes EVs as part of an electrical grid and corresponds to the first level of customer modeling. Then, I characterize demand response characteristics using *charging strategies* which map mobility requirements and other decision-relevant information (e.g., prices) to temporally differentiated charging decisions (third level of customer modeling). Note that model scope is discussed in detail in Chapter 7. As mentioned above, EVs have limited range which is often seen as one major obstacle of electric mobility. Any charging strategy thus needs to moderate between a customer's mobility requirements and other objectives. Besides this tradeoff another question for understanding EV charging behavior is the availability of relevant information on future mobility requirements and prices. Prior work has typically assumed either fully informed or uniformed decision-making. Both are somewhat implausible — full foresight of all necessary parameters will be most likely impossible while completely agnostic decision-making ignores the fundamental economic rationale

[1]The material presented in this chapter adapts and extends ideas previously developed and discussed in a series of individual research papers (Flath et al., 2013; Salah et al., 2011; Flath et al., 2012).

of customers. Using heuristic charging strategies I investigate the effect of different information regimes.

6.1 Static Characterization of Electric Vehicle Models

Currently, EV market penetration is low mainly due to the small choice of models and high purchase cost. Especially battery costs have to drop significantly in order for EVs to be able to compete with internal combustion engine vehicles without requiring special subsidies (Hidrue et al., 2011). Apart from high costs, another important reason limiting higher market shares is the range limitation of EVs. Eberle and von Helmolt (2010) coined the term *range anxiety* to describe customers' fears from EV range limitations — including both vehicle break-downs while driving as well as insufficient range for spontaneous trips (e.g., for going to the hospital). However, this fear may be over-rated as several recent studies from the USA indicate that EVs can guarantee a sufficient mobility level: Khan and Kockelman (2012) note that an EV with 160 km range could meet the driving needs of 50 % of single-vehicle households and 80 % of multiple-vehicle households. Similarly, Gonder and Markel (2007) state that only 5 % of the vehicles are driven more than 100 miles per day. Hence, range anxiety may be strongly to in adequate information of user (Flath et al., 2012). The everyday suitability of EVs in combination with future cost reductions should lead to growing vehicle penetration rates in industrialized countries over the next years.[2]

Given the limited availability of electric vehicles, one cannot readily obtain appropriate data sets to validate synthetic demand models against. To circumvent this problem, I follow the literature (e.g., Dietz et al., 2011; Sioshansi, 2012) by evaluating empirical driving profiles from conventional vehicles using technical EV specifications (battery size, charging power, consumption). For the driving data, I use weekly mobility data from a panel of German employees (Zumkeller et al., 2010). Appropriate vehicle specs are obtained from an overview of currently marketed EVs (Salah et al., 2011).

6.1.1 Driving Profiles

For short trips (e.g., commuting) it seems reasonable that car owners will maintain similar mobility behavior with EV as with internal combustion vehicles.[3] Hence, mobility panel data is a reasonable source for inferring EV charging requirements and this is the approach followed by the majority of research on EV charging modeling.

I extract driving profiles of 1,000 employees from the German Mobility Panel (Zumkeller et al., 2010). For each driving profile this data source provides the departure time, origin, arrival time and destination as well as the distance traveled

[2]Different studies estimate in the most optimistic scenarios penetration rates of 24 % (Becker et al., 2009) or 19 % (National Research Council, 2010) of the US light vehicle rate in 2030. In Europe, Nemry and Brons (2010) calculate a share between 7 % and 27 % of electric cars in the fleet by 2030.

[3]Clearly, modeling long distance trips exceeding the EV range does not yield additional insights.

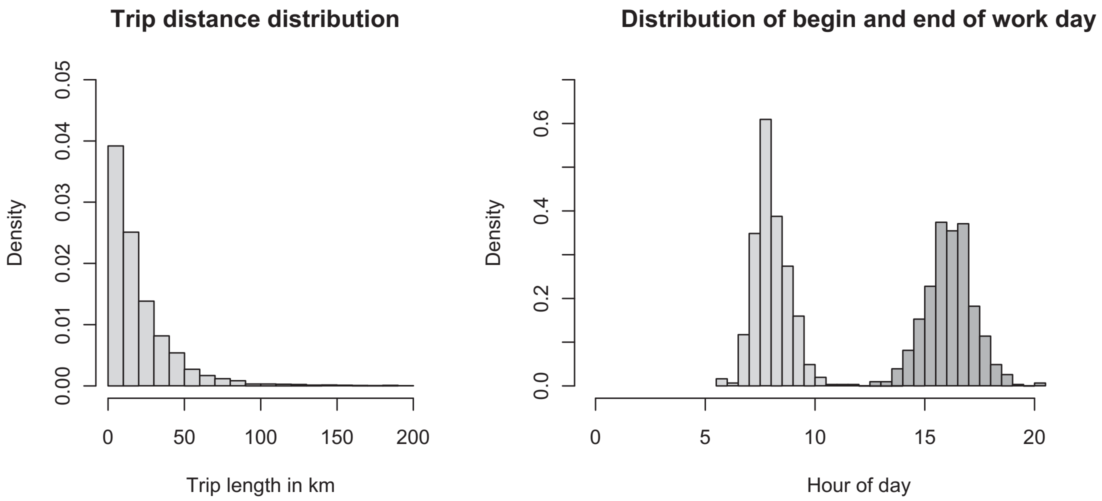


Figure 6.1: Distribution of trip lengths, begin and work day within driving profile data of 1,000 employees. (data source: Zumkeller et al., 2010)

over one week. This mobility data is available with a granularity of 15 minute intervals.

While the original driving profiles were recorded using conventional vehicles, one can use them to create fictive EV driving profiles. To do so, the driving profiles from the mobility panel are replicated assuming they were completed by (homogeneous) EVs. Such trip-level modeling clearly represents a bottom-up approach by representing individual trips as atomic model elements whereas a top-down model would assess aggregate charging loads. Presuming a certain initialization battery level one can track the EV battery State-Of-Charge (SOC) — the amount of electrical energy currently stored in the battery — over the course of time and identify charging requirements which can be mapped against the charging availability as provided by the scenario. This approach is warranted as the typical trip distances in the data set are well achievable with typical EVs (6.1).

Still, because of excessive trip distances or insufficient charging time between subsequent trips a driving profile may not be feasible with a typical EV. Under the technical specifications outlined in Sections 6.1.4 and 6.1.5, 93 infeasible driving profiles have to be removed. This leaves 907 feasible driving profiles on which the remaining analyses are based on.

6.1.2 Driving Distance Distributions and Synthetic Profiles

While empirical data records are helpful for the static evaluation of a given scenario this approach is somewhat limited for building simulation models as the set of valid driving profiles is limited in size. Therefore, I am interested in extracting the relevant statistical information from the empirical driving profiles to feed back into a generic driving model. Greene (1985) proposes to model the daily travel length of limited-range vehicles as being Gamma-distributed:

I want to apply the Gamma-fit to commuter data from the German mobility panel (Zumkeller et al., 2010). Using GNU-R[4] with the MASS package[5] a maximum likelihood estimation on trip distance distributions is perfomed. Total trip data (Figure 6.1) is fairly heterogeneous with different trip purposes such as leisure, commuting or shopping pooled. Therefore, fitting a generic distribution is not easily achieved for the whole trip set. However, the subset of unique work trip lengths indicates a good fit (see Figure 6.2). These trips are identified as direct connections from the home to the work location and vice versa. The difference to the total number of driving profiles indicates that some employees did not commute directly to the work location during the time the mobility data set was recorded.

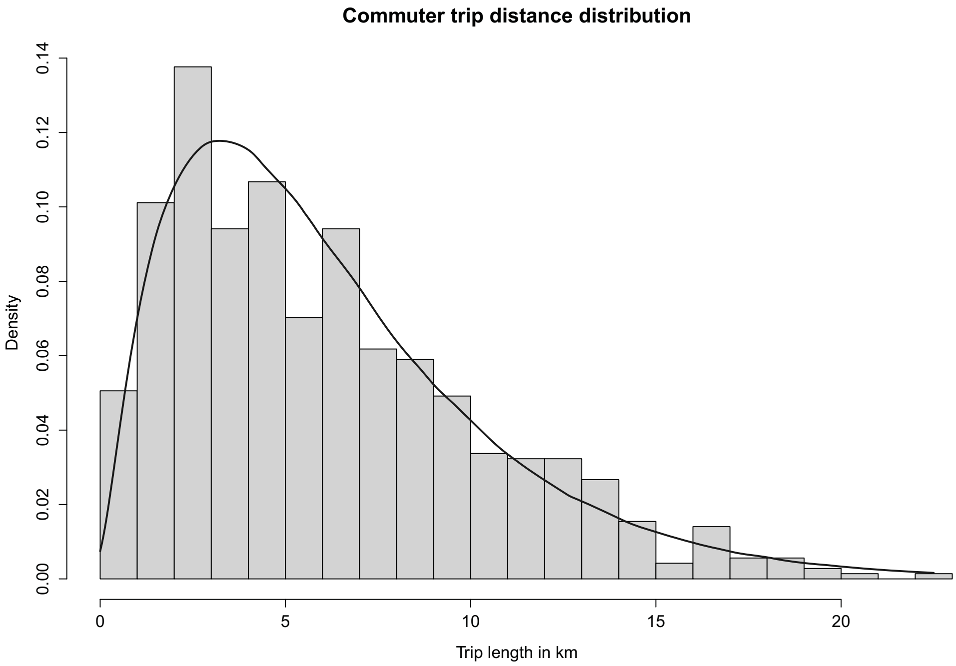


Figure 6.2: Histogram of unique commute distances and fitted Gamma distribution (data source: Zumkeller et al., 2010)

The following values for the Gamma distribution parameters shape α and scale θ are obtained as best fit:[6]

$$\alpha = 2.064 \qquad \theta = 3.034 \tag{6.1}$$

I want to further assess the adequacy of this estimated fit by looking at the first four normalized moments (see Table 6.1). All moments have the same sign and for the first three moments one obtains a very good result for the Gamma fit. Furthermore, the Kolmogorov-Smirnov statistic for the goodness of fit between the fitted Gamma distribution and the empirical data obtains as $D = 0.046$ which translates to a p-value of 0.095 exceeding the required threshold of 0.05. Hence, the Gamma distribution offers a reasonable representation of the empirical distribution of work trip lengths.

[4] `www.r-project.org`

[5] `cran.r-project.org/web/packages/MASS/index.html`

[6] The scale is often also reported as rate $\beta = \frac{1}{\theta}$.

Table 6.1: Shape parameters of empirical commuter trip data and Gamma fit

	Empirical Data	Gamma Fit
Mean	6.260	6.260
Variance	17.664	18.994
Skewness	0.923	1.392
Kurtosis	0.431	2.908

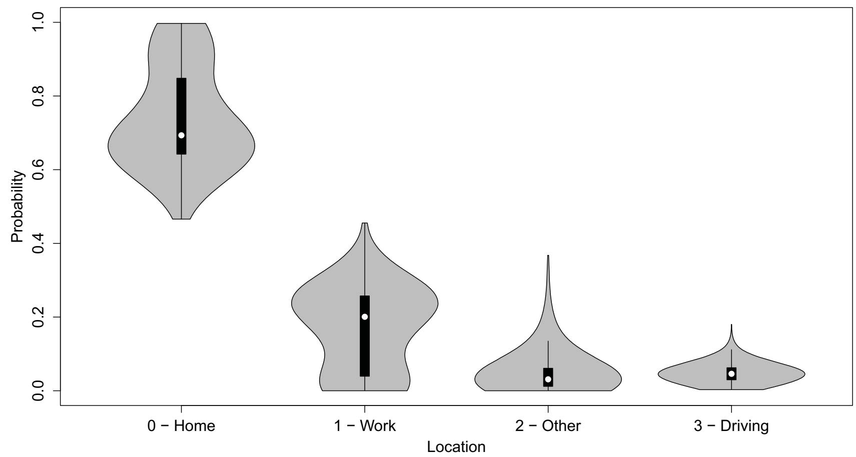


Figure 6.3: Relative share of vehicle presence at different locations (data source: Zumkeller et al., 2010)

Using synthetic distributions to model EV driving behavior facilitates the creation of scalable and yet well-calibrated models. Additionally, an analysis can readily be adapted to a different scenario by applying the corresponding distributional information. This increases model flexibility and reusability.

6.1.3 Locational Clustering

While the data set provides a multitude of vehicle locations, one can reasonably cluster these into four groups when accounting for relative probability: *Home* (0), *Work* (1), *Other* (2) and *Driving* (3). I use this numeric coding when referring to specific locations within equations. Figure 6.3 shows driving profile presence in these different states. One can directly use this locational information to infer the availability of charging services for each time slot. In line with typical EV scenarios, I only consider charging at home and at the workplace. Positing a spatial clustering among individual *Home* and *Work* locations (e.g., assuming a residential and industrial zone), one can additionally use the locational information as a proxy for tracking spatial clustering of charging activity in the distribution grid of these generic zones. This approach is similar to the analysis of residential area load as described by Rahman and Shrestha (1993) or the four-hub mobility network used by Waraich et al. (2013).

6.1.4 Vehicle Technical Data

The Mitsubishi i-MiEV was one of the first mass-produced battery electric vehicles. This sub-compact car has been produced in Japan since 2009 and sold all over the world. In the field of compact cars the Nissan Leaf has been produced since 2010. Recently, an increasing number of electric vehicles from major OEMs have become available either to customer or within field trials. The relevant characteristics for modeling EV grid loads are electricity consumption, battery capacity and vehicle maximum range. Table 6.2 lists this data for a selection of current electric vehicles. For my model I deviate from original EV specifications and rather use a fictitious vehicle. The rationale here is to better reflect the potential capabilities of future standard EVs.

Table 6.2: Technical data of current electric vehicles (Salah et al., 2011)

Make and Model	Curb Weight (kg)	Battery Capacity (kWh)	Range (km)	Consumption (kWh/km)
Citroën C-Zero	1,110	16	150	0.107
Ford Transit Electric	2,340	28	130	0.215
Karabag Fiat 500 E	1,120	20	140	0.148
Mercedes A-Class E-Cell	1,591	36	255	0.141
Mitsubishi i-MiEV	1,110	16	150	0.107
Nissan Leaf	1,520	24	160	0.150
Peugeot iOn	1,110	16	150	0.107
Renault Fluence Z.E.	1,610	22	185	0.119
Renault Kangoo Z.E.	1,410	22	170	0.129
Renault Twizzy 75	450	7	100	0.070
Renault Zoe	1,392	22	210	0.105
Smart Fortwo Electric Drive	975	17.6	140	0.126
Tesla Roadster	1,220	53	393	0.135
Think Global Th!nk City	1,038	23	160	0.144
Average	*1,285*	*23*	*178*	*0.129*

While one would expect a direct relation between weight and consumption (cf. Knitte, 2011), this relationship is only confirmed by the data if both the Renault Twizzy and Ford Transit Electric (the lightest and the heaviest vehicle) are considered (see Figure 6.4). Therefore, I do not consider a weight-consumption relationship when creating the generic EV model and rather assume a consumption value of 0.129 $\frac{kWh}{km}$ in the model (reflecting the average value). This simplification establishes a direct correspondence between range and given battery size, i.e. vehicle range will increase for larger battery size while in reality the extra weight from the battery would increase consumption and thus dampen the range increase. Note that I further simplify by using a singular consumption value per kilometer while in reality this consumption value will heavily depend on external factors such as temperature, vehicle speed or the height profile of the route. Abstracting from these complexities, I focus on a single EV specification with 30kWh battery capacity and a static consumption value of 0.129 $\frac{kWh}{km}$.

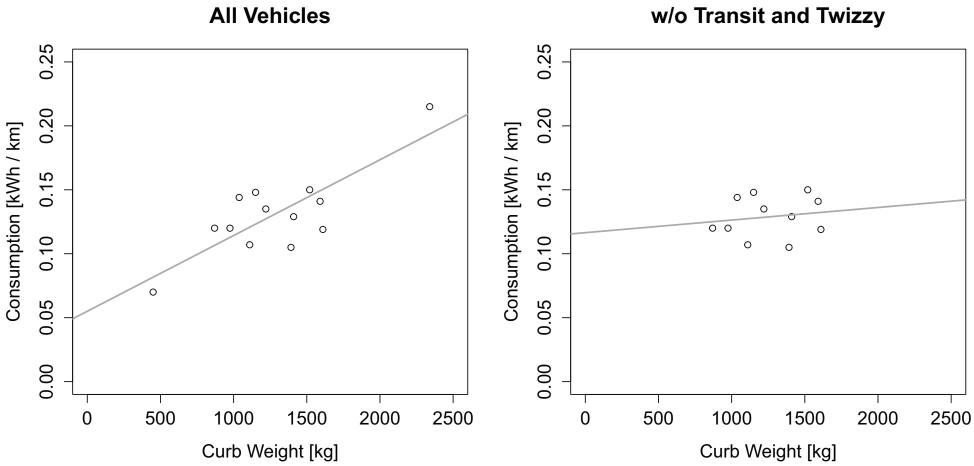


Figure 6.4: Relationship between EV range and consumption (data source: Salah et al., 2011)

6.1.5 Charging System Specification

The IEC standard 61851-1 specifies a set of modes for EV charging.[7] These encompass AC 16 Ampere 1-phase charging (3.7 kW), 16 Ampere 3-phase charging (11 kW) as well as 32 Ampere 1-phase charging (7.4 kW) and 32 Ampere 3-phase charging (22 kW). I mostly focus on the 11 kW mode which results in a charging time of about 165 minutes for a complete charge of a 30 kWh-battery. Furthermore the standard describes fast Direct Current (DC) charging with currents up to 450 Ampere. To match the temporal resolution of driving profiles I discretize the charging process using 15 minutes segments and assume a linear charging process. This translates to a maximum charge amount of $\overline{\phi} = 2.75$ kWh per time slot for the 11 kW case. Table 6.3 summarizes the different modes and provides the corresponding $\overline{\phi}$ values. For illustration purposes, I also include DC charging but will not consider this mode in the remainder.

Table 6.3: Charging modes as specified by IEC standard 61851-1

Mode	AC/DC	CPS[8]	Current	Phases	Power	$\overline{\phi}$
1	AC	no	$\leq 16A$	1	$3.7kW$	0.925
1	AC	no	$\leq 16A$	3	$11kW$	2.75
2,3	AC	yes	$\leq 32A$	1	$7.4kW$	1.85
2,3	AC	yes	$\leq 32A$	3	$22kW$	5.5
4	DC	yes	$\leq 450A$	n/a	$\leq 90kW$	≤ 22.5

Another technical aspect are losses in the charging process. These losses scale quadratically in charging current ($P_{loss} = I^2R$). Consequently, there is a trade-off between charging speed and charging efficiency. However, internal resistance of modern batteries is very low. Krieger and Arnold (2012) as well as Amoroso and Cappuccino (2012) report a limited decline in charging efficiency for C-rates (capacity-

[7]Figure E.1 in the Appendix summarizes the specified modes
[8]Control Pilot Signal

normalized charging speed $\frac{\text{battery capacity}}{1h}$) below 1.0 with efficiency ranging from 0.99 at 0.1 C to 0.91 at 1.0 C. Compared to the large fluctuations in wholesale electricity prices, this efficiency drop has a limited effect on optimal charging policies for the different IEC charging modes (C-rates between 0.12 and 0.73). Therefore, I abstract from charging losses and assume a loss-free charging process with efficiency $\eta = 1$. When analyzing even higher charging speeds exceeding 1.0 C (i.e., greater than 30 kW), these power-dependent losses should no longer be neglected.

6.1.6 Wholesale prices

To incentivize the shifting of EV charging loads time-based electricity prices are assumed. For the model I use hourly electricity prices from the EPEX spot market.[9] These include neither taxes nor license or transmission fees. For sake of exposition, the average hourly prices of 2010 are normalized to the average retail electricity price in Germany in the same year (0.237 €/kWh). To better map hourly prices to the 15-minute resolution of the driving profiles, the hourly wholesale prices are linearly interpolated on the same interval. Figure 6.5 depicts the upscaled and interpolated electricity prices for one week. This approach follows prior research on smart grid and EV applications (Hartmann and Özdemir, 2011; Gottwalt et al., 2011). Due to the merit-order effect, the wholesale price can also be considered as a proxy for the availability of low-cost renewable generation within the power system (Sensfuss et al., 2008). Consequently, EV charging should ideally occur in low-price periods, both from an economic and ecologic perspective.

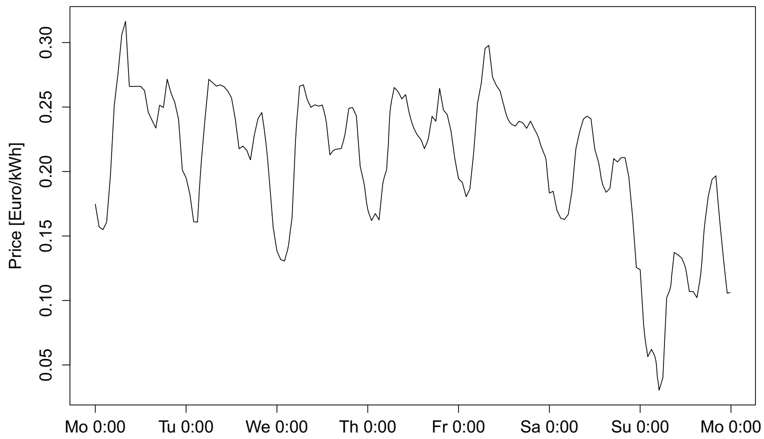


Figure 6.5: Upscaled and interpolated EPEX Spot prices 2010

6.2 A Formalized Electric Vehicle Charging Model

An empirical or synthetic driving profile yields a consumption vector $\gamma^i = \langle \gamma_1^i, ..., \gamma_T^i \rangle$ as well as a location vector $\mathbf{l}^i = \langle l_1^i, ..., l_T^i \rangle$ which form the static basis of modeling an electric vehicle. The consumption vector specifies the required electrical energy for driving for each time slot while the location vector indicates a ve-

[9] www.epexspot.com/en/market-data/

hicle's current location l_t^i over the collection of time slots $t \in [1..T]$. This decision vector constitutes the dynamic load behavior. The time horizon also spans a (potentially dynamic) price vector $\mathbf{c} = \langle c_1, ..., c_T \rangle$ indicating the price of electricity at each point in time. Given this discrete time structure, the EVs' charging decisions can be represented as charging vectors $\phi^i = \langle \phi_1^i, ... \phi_T^i \rangle$.[10] The total load at location x at time t then obtains as

$$\Phi_{t,x} = \sum_{i=1}^{n} \left[\left(\mathbf{l}_t^i \phi_t^i \right) \mathbf{1}(x = l_t^i) \right]$$

where $\mathbf{1}(\cdot)$ is the indicator function of event $(\cdot)$. Following the time resolution of the EV profiles, all consumption (driving) and charging actions are discretized on a 15-minute interval. Hence, I model the time horizon as a collection of 15-minute time slots. Table E.1 in the Appendix provides a summary of the model nomenclature.

I represent individual charging behavior in the form of charging strategies. In the literature on economic EV grid integration, charging strategies are a central concept for characterizing EV charging schedules. A charging strategy determines when and how much to charge based on currently available information. The fundamental trade-off in this decision is between flexibility of mobility and availability of the vehicle on the one hand and cost savings, system compliance, sustainability goals or other objectives on the other hand. Following the DSM notion of price signals I focus on economic EV charging strategies that optimize charging costs while enforcing vehicle availability for planned trips as a constraint. However, the modeling approach can equivalently be applied when considering alternative objective functions. This is discussed in Section 6.4.2.

Definition 6.1 [Economic charging strategy]. *An economic charging strategy determines individual charging amounts given the driving profile and electricity costs, that is a mapping* $(\gamma^i, \mathbf{l}^i, \mathbf{c}) \mapsto \phi^i$.

Within the research on EV integration and coordination two polar charging strategies are typically identified: *simple charging* (Lopes et al., 2009) and *optimal smart charging* (Sioshansi et al., 2010; Dietz et al., 2011). In the first regime EVs are always charged when they are connected to the grid, while in the second regime car operators derive a cost-minimal charging program fulfilling the mobility requirements. This optimal solution is typically obtained under the assumption of perfect foresight with respect to electricity prices and future mobility requirements. Clearly, for realistic modeling the perfect knowledge assumption is not directly applicable. To moderate these limitations, I develop heuristic charging strategies requiring limited information inputs.

6.3 Simple Charging Protocol

The simplest strategy for electric vehicles is to charge the battery whenever possible, i.e., independent of any other decision factors like battery SOC or charging costs.

[10] When referring to individual vehicle decisions I will sometimes drop the i index from γ^i and ϕ^i for ease of exposition.

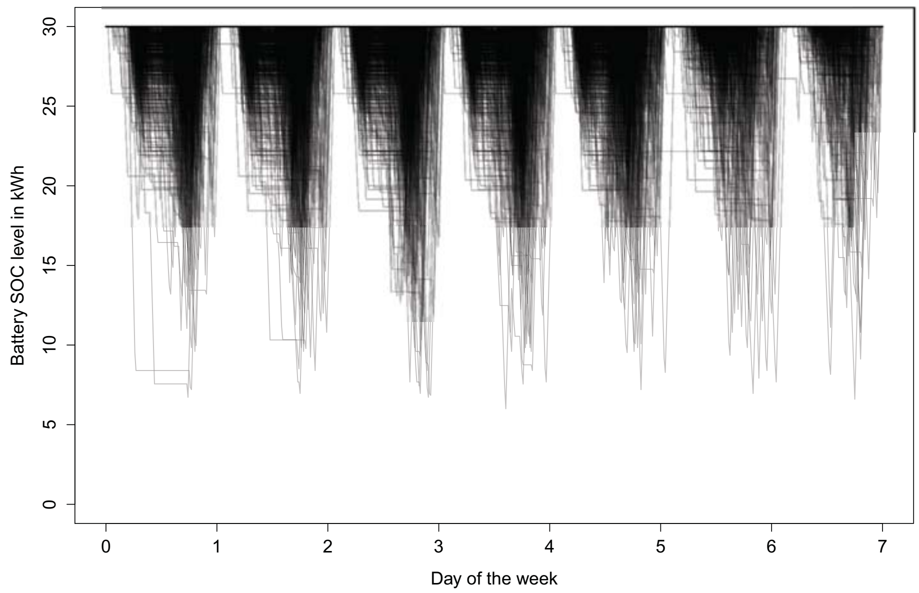


Figure 6.6: Battery level evolution of electric vehicle population under as fast as possible charging (*charging at home, one week*)

This As Fast As Possible Charging Strategy (AFAP) approach is often referred to as "dumb" or "naïve" charging. Under this charging protocol drivers initialize the EV charge process at maximum power directly after arriving at a location where charging is possible. A key property of AFAP charging is the fact that it maximizes EV range:

Proposition 6.1. *As Fast as Possible charging maximizes an electric vehicle's range at any given time.*

Proof. AFAP charging will always choose the largest charging amount possible. Consequently, no other charging protocol can achieve a higher battery level and thus vehicle range is maximized. □

Moreover, AFAP charging requires no information on future trips of the EV user. Therefore, one can reinterpret Proposition 6.1 and use the AFAP protocol to analyze the feasibility of any given driving profile under EV battery restrictions. At the same time simple charging is completely static and cannot be influenced by external signals (e.g., price, congestion or renewable generation signal). Intelligent charging strategies need to improve on this minimal strategy with respect to these objectives while maintaining the same vehicle availability. Figure 6.6 illustrates the SOC across driving profiles under simple charging behavior. The distinct clustering in the upper third of the diagram illustrates the regularity of mobility patterns across a large number of driving profiles. The very light coloring of the lower diagram section illustrates that only a very small fraction of a 30kWh EV battery is actually used across the population.

Figure 6.7 illustrates the resulting average charging costs for the EV population in selected weeks using the EPEX-based pricing as described above. The costs graphs are distinctly skewed and resemble the graphs put forward by Faruqui (2010). This analysis confirms that there are instant winners and losers when introducing RTP electricity rates under AFAP charging. Furthermore, these results are robust to the selected price week.

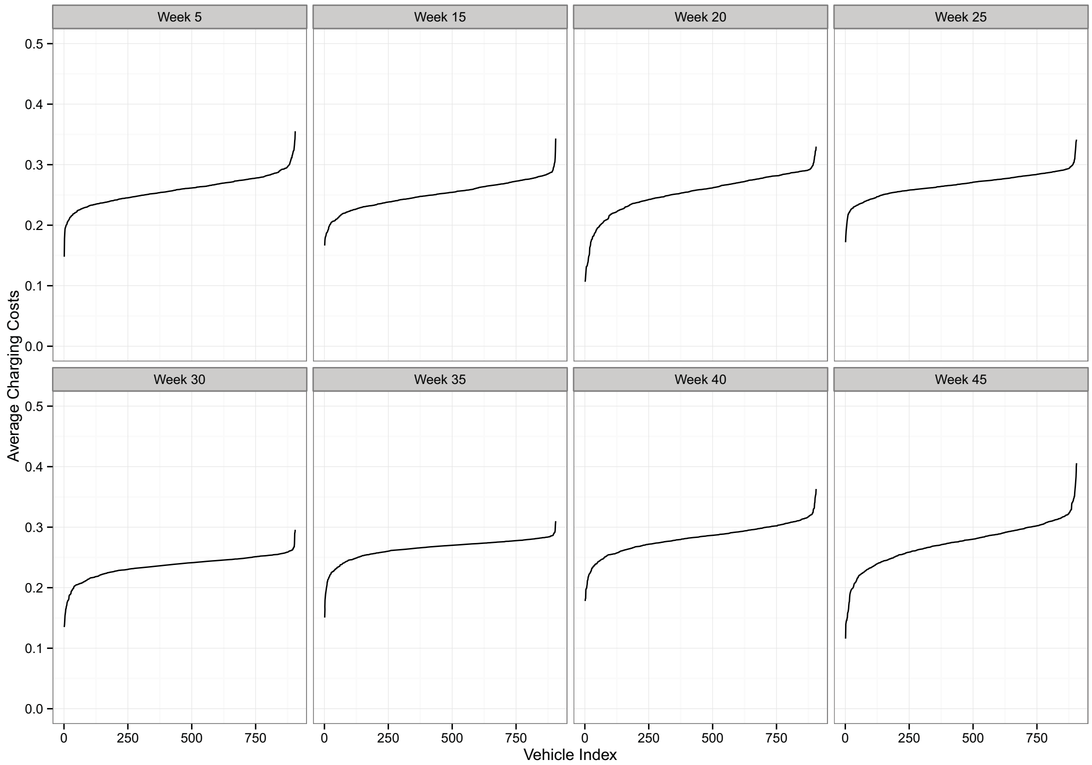


Figure 6.7: Comparison of average AFAP charging costs

In the literature AFAP charging is often used as the reference case for uncoordinated charging behavior. It is also most applicable if drivers are not offered economic incentives for charging flexibility, i.e. in the absence of time-variable electricity prices. Some extensions to the simple charging protocol have been proposed: Lopes et al. (2009) allow charging only when the standing time exceeds four hours while Qian et al. (2011) allow charging only during nighttime.

6.4 Optimal Smart Charging

Previous work on economic EV charging optimization typically formulates the optimal charging problem as a linear program (Dietz et al., 2011; Sioshansi, 2012). The objective is to minimize total charging costs subject to meeting mobility requirements as specified by a statistical driving profile as well as charging and battery capacity constraints. These models yield the cost-minimal charging pattern for realizing the mobility needs of any feasible driving profile. Denoting the initial battery level by SOC_0, battery capacity by $\overline{SOC}$ and the maximum charging amount in one time slot by $\bar{\phi}$, the following linear program obtains:

$$\min_{\phi} \sum_{t=1}^{T} (c_t \cdot \phi_t) \tag{6.2}$$

subject to:

$$0 \leq SOC_t \leq \overline{SOC} \; \forall t \in [1..T] \tag{6.3}$$

$$0 \leq \phi_t \leq \kappa(l_t) \; \forall t \in [1..T] \tag{6.4}$$

$$\text{where} \quad \kappa(l_t) = \begin{cases} \bar{\phi} & \text{if charging is possible at location } l_t, \\ 0 & \text{otherwise.} \end{cases} \tag{6.5}$$

$$SOC_t = SOC_{t-1} + \phi_t - \gamma_t \; \forall t \in [2..T] \tag{6.6}$$

$$SOC_T = SOC_0 \tag{6.7}$$

Equation (6.2) is the objective function which in this case corresponds to minimizing total charging costs. The objective function is easily adapted to alternative optimization goals, e.g., minimizing emissions or maximizing battery life. Equation (6.3) ensures the battery level remains within the proper range, Equations (6.4) and (6.5) reflect the charging capability at the current location (charging availability and charging speed) and Equation (6.6) is the storage carry-over condition capturing the temporal interdependence between time slots. Furthermore, one needs to specify a terminal SOC level to avoid complete discharging at the end of the optimization horizon (6.7). The OPL optimization code is provided in the Appendix (Algorithm E.1). Figure 6.8 illustrates the individual average charging costs in the EV for selected price weeks. Compared to 6.7, the curves are much lower illustrating the substantial economic potential of smart charging. Furthermore, the curves are flatter. Therefore, the RTP fairness issues raised by Faruqui (2010) are less pronounced in the presence of highly flexible demand. This is an important finding concerning possible acceptance issues of RTP pricing schemes.

6.4.1 Smart Charging Modifications

The optimization program clearly requires perfect knowledge of both future power prices as well as the vehicle's future trips. Additionally, greedy optimization behavior will exploit the minimum allowed battery level in Equation (6.3) to react to later low price realizations. While this behavior does not violate the optimization constraints it will significantly reduce the vehicle's availability level for spontaneous trips. Both the perfect information requirement and the reduction of spontaneous EV range limit the practical relevance of optimal smart charging. Relying on these optimal results one may, therefore, overestimate the impact from economic charging

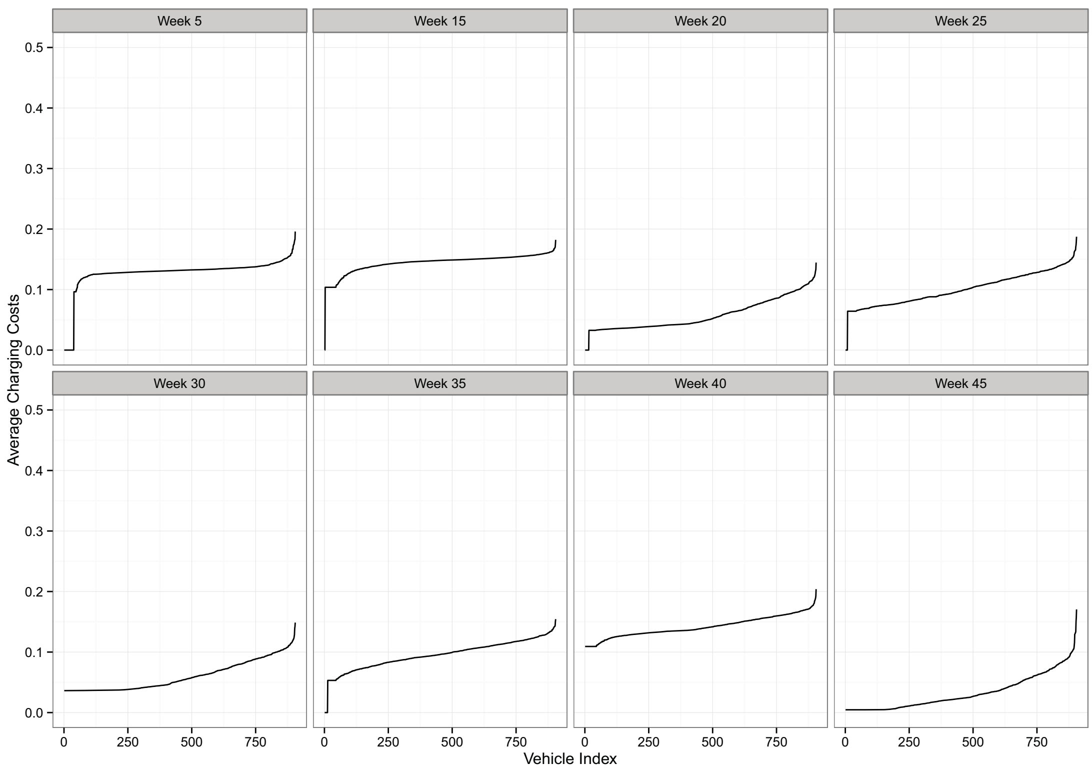


Figure 6.8: Comparison of average optimal smart charging costs

coordination. Still, the results from optimal smart charging provide a robust upper bound to benchmark alternative strategies against. In the following subsections, I suggest two modifications of the optimization program which ensure (i) a minimum vehicle availability level (countering range anxiety) and (ii) reflect limited knowledge of future prices to increase the practical applicability of optimal smart charging. Flath et al. (2012) argue that such modifications or appropriate heuristics are crucial elements for developing robust EV DSS.

Minimum Battery Level

As noted before, range anxiety is commonly considered a major adoption obstacle for range-limited vehicles. The linear optimization program as specified above does not reflect this critical issue. More drastically, the optimal charging policy typically exhibits regular discharging down to SOC levels of 0 to fully leverage later low price occurrences. Such SOC trajectories may be highly discomforting from a user's perspective.

Ideally, one wants to counter such undesired behavior by requiring the charging policy to recharge the vehicle when the battery SOC drops below a certain level, $\underline{SOC}$. Clearly, one cannot simply enforce $SOC > \underline{SOC}$ for all $t \in [0..T]$ as this would be equivalent to never using the battery capacity between 0 and $\underline{SOC}$ — i.e. reducing the usable battery capacity from $\overline{SOC}$ to $\overline{SOC} - \underline{SOC}$. Furthermore, I want to retain the linear properties of the optimization problem and thus want to avoid the use of logical "if/ else" constraints.[11] One can achieve the desired result of triggering charging activity below $\underline{SOC}$ when possible by adding an additional constraint to the linear program.

$$\phi_t \geq \frac{\kappa_t \cdot (\underline{SOC} - SOC_{t-1})}{\underline{SOC}} \quad \forall t \in [0..T] \tag{6.8}$$

The above formulation retains the linear program properties which facilitates efficient computation. The charging amount enforced from securing the minimum charge levels varies with the difference between SOC_t and $\underline{SOC}$ — the farther below the threshold the current battery level is, the higher is the enforced charging amount.

This also reflects behavioral aspects as the urgency of recharging will typically be greater at low SOC levels. Figure 6.9 illustrates the effect on exemplary SOC trajectories from 30 kWh battery packs. In the $\underline{SOC} = 0.1$ and $\underline{SOC} = 0.2$ cases the resulting trajectory charts are almost identical to the case of optimal charging with a 22.5 kWh battery — the optimal minimum battery level aware charging policy avoids reaching levels below this threshold level by securing an sufficiently high level before a driving discharge. That is, the policy will tend to over-provision prior to trips compared to optimal charging without minimum battery level. Clearly, this is exactly what we were looking for in the first place — a limited amount of additional charging guaranteeing a certain level of EV availability at most times. For increasing minimum battery levels, one can observe a larger number of trajectories where the SOC undershoots the minimum level over the course of the week.[12] However, the number still remains fairly limited even at a very high threshold level of 50% with the majority of driving profiles not dropping below the minimum battery level.

These results suggest that most drivers can achieve their typical driving behavior with much lower total vehicle range than typically expected.[13] More importantly, it also implies that smart charging with minimum SOC level can greatly increase EV standby range without sacrificing the potentials of cost-oriented smart charging. Furthermore, minimum range requirements help to apply optimal smart charging in situations with prevalent trip uncertainty: Then, the amount of minimum spontaneous range required corresponds with an expectation over "surprise trip requirements". This observation offers new perspectives and extension possibilities as one could dynamically adjust the minimum range requirement, e.g., to account for temporal fluctuations of driving uncertainty.

[11]Such logical constructs are easily introduced in optimization languages such as ILOG OPL, but will inevitably turn the optimization problem into a computationally more demanding mixed-integer program.

[12]Note how each occurrence of "forced charging" fully exploits the smooth approach from below as permitted by Equation (6.8).

[13]This result is in line with the observations by Gonder and Markel (2007) or Pearre et al. (2011).

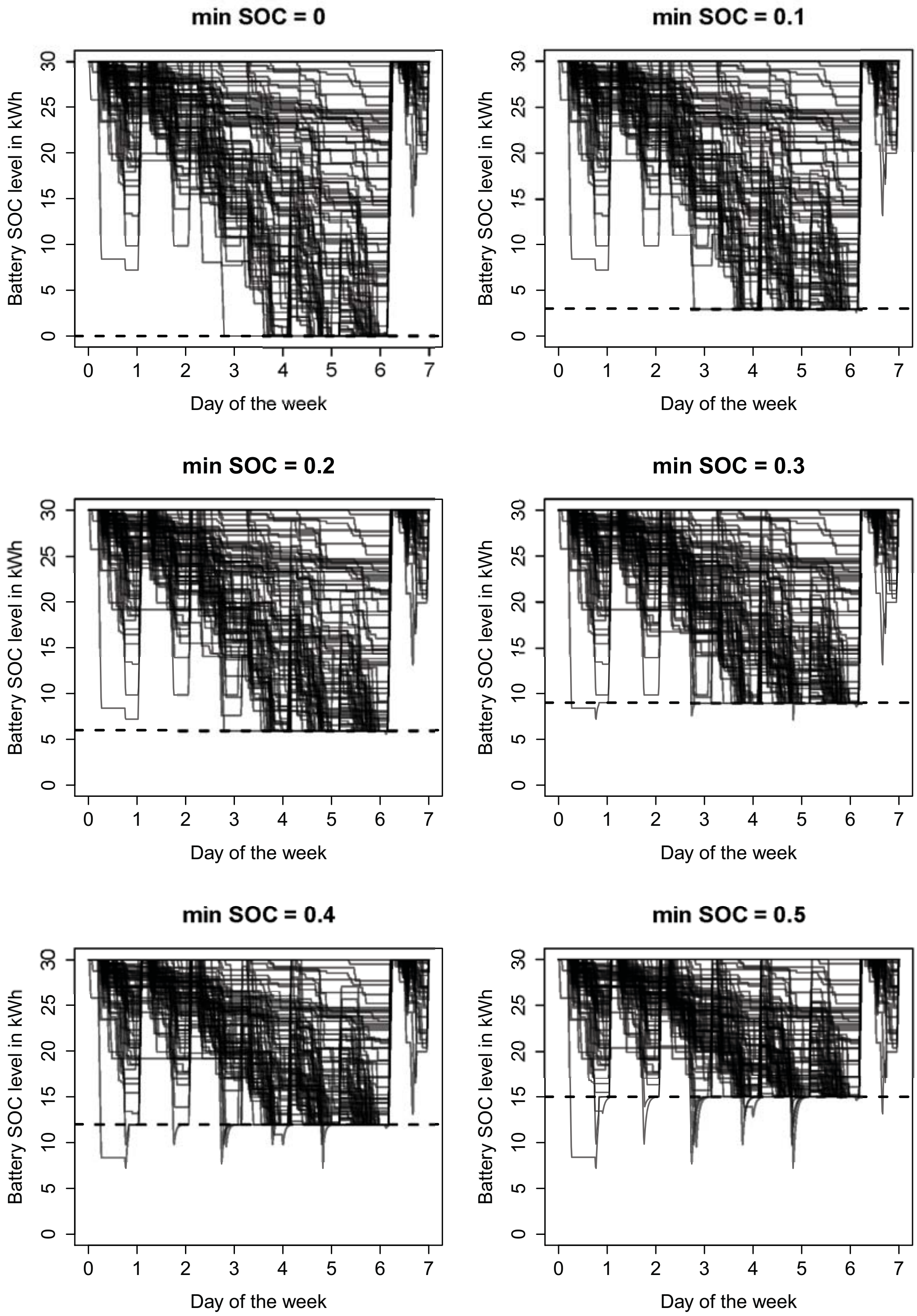


Figure 6.9: Cost-optimal SOC trajectories for different minimum thresholds

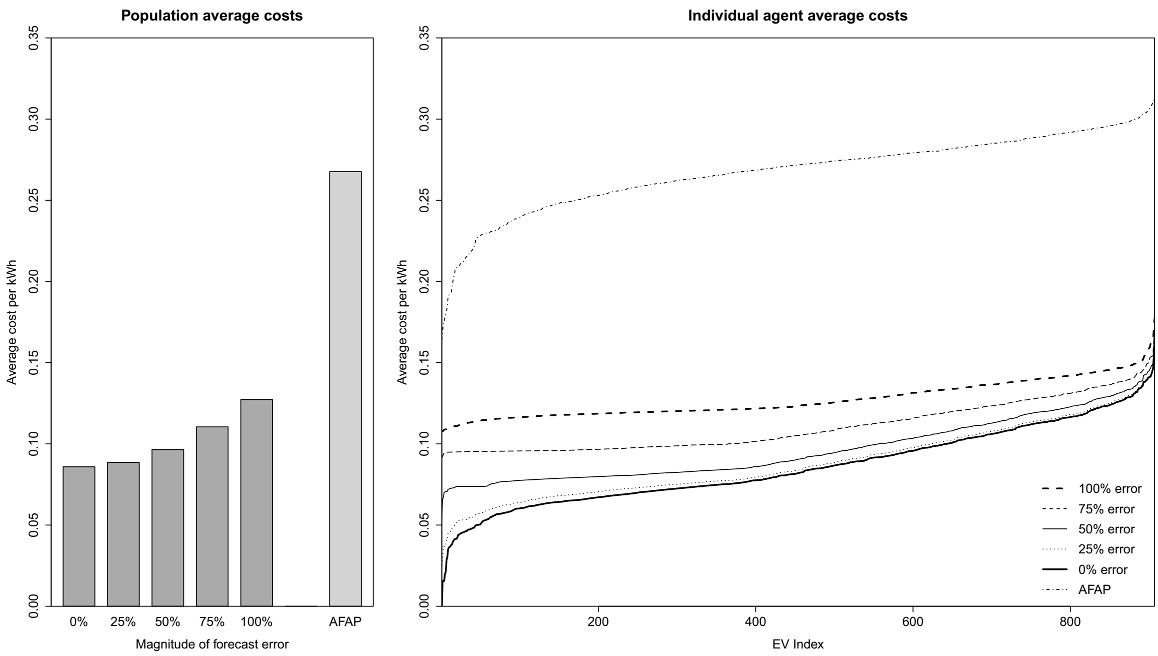


Figure 6.10: Impact of price information on charging costs

Price Backcasting

Given the highly stochastic behavior of electricity prices, the perfect information assumption underlying optimal smart charging is difficult to justify. Sioshansi et al. (2009) address a similar forecasting problem for the operation of centralized electricity storage systems. They use "stale" prices from the prior week to derive the optimal policy and evaluate its effectiveness using the prices of the current week. Due to regular weekly price patterns and stable operation patterns, large storage systems achieve approximately 80% of optimal profits under price backcasting. Optimal EV charging occurs in a more "spikey" fashion than pumped-hydro plan operations — i.e., the charger is mostly idle except for a few very low cost time slots when charging occurs. This may limit the potential of backcasting for EV charging optimization. To moderate this problem, I modify the Sioshansi et al. (2009) approach by using fictive price vectors obtained as weighted linear combinations of the past and the future price vector.[14] In a practical implementation such updates could be near-time weather or demand forecasts indicating when lower electricity prices will be more likely to occur. The linear mix of backcast and forward-looking prices aims to mimic this relation.

Using a one year run with the 2010 EPEX prices and looping the weekly driving profiles I evaluate the cost impact of impairing price information: Figure 6.10 shows that the charging cost are greatly improved by introducing these fictive price vectors derived from linear combinations of past and future prices. Compared to the charging costs under AFAP charging the results remain very good even for pure backcasting without the "forecast element". Therefore, baseline weekly price pat-

[14] Alternative approaches to modeling this price uncertainty would be direct modeling of forecast errors (Ahlert and Block, 2010; Ahlert, 2010) or using stochastic price processes (Möst and Keles, 2010; Keles et al., 2012).

terns seem to be sufficiently stable with limited information being able to capture the concrete differences between the current and the prior week. The inter-agent cost analysis (right panel) indicates that reduced forecast quality will especially impact those agents that incur the lowest charging costs. This makes sense as low average costs obtain from precise targeting of very select time slots of very low price events. Given the large improvement over naïve charging, I argue that one can achieve smart charging decisions with limited price information.

6.4.2 Alternative Objectives and Charging Losses

Optimal smart charging as specified above is clearly not restricted to cost optimization but can also serve to achieve other charging goals such as optimizing battery health or maximizing usage of available renewable generation. In this section I address optimization goals that are influenced by a temporally varying external signal as well as full endogenous objectives that are exclusively influenced by the selected charging policy. Similarly, as indicated in Section 6.1.5 charging losses may be of relevance for higher charging speed levels. Consequently, these need to be accounted for in the smart charging protocol.

Alternative Temporal Optimization Goals

The charging cost vector c used above was motivated by temporal electricity pricing (i.e. TOU or RTP). However, for the optimization this vector only serves as a ranking over time slots. If an alternative optimization goal can be characterized in a similar fashion in the sense of differentiated charging suitability across time, these alternative goals can be tackled with the identical optimization program by adopting c accordingly. Schuller et al. (2012) use different charging cost vectors to establish "green" charging strategies which achieve a high utilization of available renewable generation. One can similarly represent "system-conformity", i.e. grid usage levels. Clearly, purely cost-based optimization will also capture these effects to a certain extent as wholesale prices are influenced by both system-wide demand and supply matching as well as the availability of renewable generation (Sensfuss et al., 2008).

Incorporating Battery Health

Given its greedy nature optimal smart charging gives rise to a distinct "bang-bang" policy with respect to charging amounts — either charging at the maximum possible charging or not charging at all. Bashash et al. (2011) note that high charging currents (and consequently high charging power levels) can substantially harm battery health.[15] This will reduce battery life which has significant impact on EV total life-cycle costs. Following Ahlert (2010) battery usage costs should be evaluated in monetary terms and appropriately accounted for in an integrated objective function (Equation 6.2) acknowledging both types of costs — battery usage and charging

[15]The authors also note that deep discharges and full charges are harmful for battery management but to a lesser extent than the charging current.

costs. Bashash et al. (2011) note that there is a quadratic impact of charging power on battery health. Reflecting this effect using a "damage term", $d_t = \chi\phi_t^2$, yields a quadratic optimization problem which is computationally more involved than the linear program above:

$$\min_{\phi} \sum_{t=1}^{T} \left[(c_t + \chi\phi_t)\, \phi_t \right] \tag{6.9}$$

Intuitively, extreme charging levels are typically avoided under this battery-health optimized charging regime and charging occurs at more moderated levels. Still, large price variations in the electricity market will still induce noticeable "swings" in charging behavior. When concerned with a single optimization problem, i.e. an individual vehicle optimization, battery health aspects should be accounted for when determining optimal charging policies. When modeling a large population the additional computational burden of solving quadratic programs may exceed the added insights. Furthermore, the relevant battery damage and cost parameters will typically be vehicle-specific and a generic parametrization will yield somewhat arbitrary results. Therefore, the following analyses will abstract from battery health implications.

Minimizing Charging Power

An alternative approach to optimizing battery health is minimizing the maximum charging power level. It is fairly straight-forward to adopt the linear program from Section 6.4 to reflect this alternative optimization goal while still retaining the program's linearity. I replace the objective function (6.2) and aim to minimize the value of $maxLoad(T)$ which indicates highest charging power value occurred over the optimization horizon:

$$\min_{\phi}\ maxLoad(T) \tag{6.10}$$

In addition one needs to ensure that $maxLoad(T)$ does indeed attain the highest load value that occured over the course of the optimization horizon, that is

$$maxLoad(t) \geq maxLoad(t-1)\ \forall t \in [2..T]\,. \tag{6.11}$$

Similarly, at any point in time the current $maxLoad$ value must be greater than the current charging load:

$$maxLoad(t) \geq \phi_t\ \forall t \in [1..T] \tag{6.12}$$

The OPL optimization code is provided in the Appendix (Algorithm E.2).

Besides establishing a battery-conscious charging profile this optimization result also indicates the minimum charging power level at which a driving profile remains feasible. With a mean of 0.287 kW[16] one observes fairly low values compared to the IEC specifications (Section 6.1.5). As one would expect, this value depends to a great

[16] Quantile values are as follows: 1st Qu. 0.081 kW, Median 0.184 kW, 3rd Qu. 0.352 kW

amount on the driving profiles' weekly driving amount as depicted in Figure 6.11. Said low charging power requirements indicate that one can tap on a considerable flexibility pool through EV charging coordination. However, one needs to bear in mind that these results obtain under full foresight and are based on driving profiles with a weekly horizon.

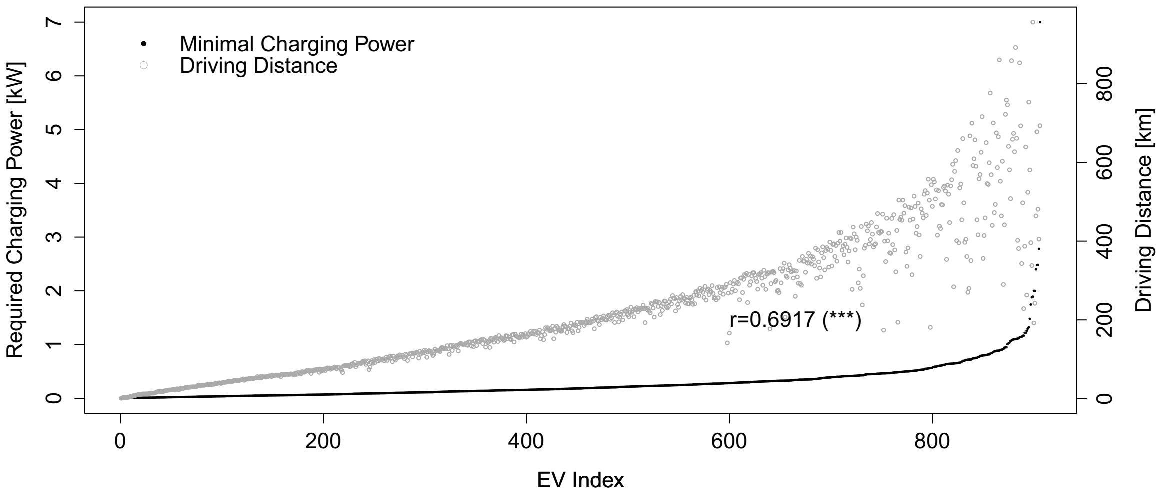


Figure 6.11: Charging power required for EV profile feasibility and driving distance

Recognizing that the minimal maximum charging load also indicates the grid capacity required by a given EV profile, this analysis can also be applied to assess grid impacts. When incorporating *demand charges* for capacity usage one can characterize the optimal trade-off between charging costs stemming from variable electricity pricing (c_t) and *demand charges DC*,

$$\min_{\phi} \sum_{t=1}^{T} (c_t \phi_t) + DC \cdot maxLoad(T). \tag{6.13}$$

While rate specifications implementing both dynamic pricing as well as demand charges are not yet being offered, they seem to be a viable option. Already today, some grid operators offer differentiated pricing of charging services dependent on the charging power (and location).[17]

Loss-Aware Charging

To capture power-dependent charging losses in the model, an effective charging amount $\tilde{\phi}_t$ needs to be introduced for usage in the storage constraint (6.6). The value of $\tilde{\phi}_t$ is constrained by efficiency as a function of charging speed, $\eta(\phi_t)$: $\tilde{\phi}_t \leq \phi_t \eta(\phi_t)$. Under a linear relationship between efficiency and charging speed the program will become quadratic. Given the limited scale of these losses (see Section 6.1.5) and the

[17] `www.enbw.com/content/de/privatkunden/innovative_tech/e_mobility/elektronauten-ladekarte/120425_Fly_Ladekarte_Onl_mSt_31-8__2_.pdf`

reduced optimization performance of the quadratic program I restrict the analysis to a loss-free model ($\tilde{\phi}_t \equiv \phi_t$).

6.5 Heuristic Smart Charging

While optimal smart charging fully endogenizes incentives as well as vehicle status, it is difficult to implement in practice as it relies on full foresight of future trip information. I want to complement prior work on EV charging strategies with a notion of smart charging based on a heuristic strategy. Unlike optimal smart charging the heuristic smart charging decisions should not depend on perfect knowledge of future prices and trip plans but should rather condition decisions on currently available information (e.g., charging price, battery state-of-charge). However, by waiving charging opportunities and thus departing from the naïve as fast as possible strategy one runs the risk of the EV not being available at the beginning of a trip. This observation is summarized in Proposition 6.2.

Proposition 6.2. *Without advance information on an upcoming trip any non-AFAP charging strategy cannot guarantee the same driving profile feasibility as simple AFAP charging.*

Proof. AFAP charging maintains the maximum spontaneous range at any point in time (Proposition 6.1). When departing from AFAP behavior one consequently loses spontaneous range. Thus, one can trivially construct a driving profile with a surprise long-distance trip which is feasible under AFAP charging but not under uninformed non-AFAP charging which proves the claim. □

Given this proposition, one needs to provide some form of advance information to guarantee the same profile feasibility as achieved by simple AFAP for non-AFAP charging protocols. More specifically, one needs to know the required battery level and the departure time of an upcoming trip. Given this information, an alternative charging protocol will ensure this goal battery level before the time of departure and thus guarantee vehicle availability.

6.5.1 As Late as Possible Charging

Following Proposition 6.2, one need to provide at least some limited foresight into the upcoming trip to ensure profile feasibility with non-AFAP charging. One can achieve this by specifying a critical SOC level SOC_t^* for each time slot using Algorithm 6.1. Whenever SOC_t is below SOC_t^* the EV will require a charging amount $\phi_t = SOC_t^* - SOC_t$ to be able to complete its next trip. I refer to this charging approach as the As Late As Possible Charging Strategy (ALAP). This is because it ensures driving availability "as late as possible". Due to the SOC_t^* determination taking into account charging availability, the resulting charging amounts are solely derived by comparing the current SOC level to the current critical SOC level:

$$\phi_t^{ALAP} = \max\{0, SOC_t^* - SOC_t\} \tag{6.14}$$

Algorithm 6.1 Critical SOC determination for ALAP charging

$SOC^*_T = SOC_0$
for $t = T$ to 1 **do**
  if $\gamma_t > 0$ **then**
    $SOC^*_{t-1} = SOC^*_t + \gamma_t$
  else if $\kappa_t = 0$ **then**
    $SOC^*_{t-1} = SOC^*_t$
  else if $SOC^*_t > \kappa_t$ **then**
    $SOC^*_{t-1} = SOC^*_t - \kappa_t$
  else
    $SOC^*_{t-1} = 0$

The left panel of Figure 6.12 illustrates the determination of SOC^*_t prior to a trip. However, for some driving profiles knowledge of multiple future trips may be required as charging during the parking period between two trips may not always be possible or parking times may not be sufficient to reach SOC^*_t, especially for low $\bar{\phi}$ values. The right panel of Figure 6.12 depicts this situation: Here, knowledge of three trips is required. Prior to trip 3 the vehicle cannot be charged and before trip 2 parking time is too short, resulting in an increase of SOC^*_t prior to trip 1.

Clearly, real-world applicability of ALAP charging hinges on how far ahead one needs to plan to determine SOC^*_t. This "lookahead time" is driven by the charging speed as well as the availability of charging spots. Table 6.4 provides an overview of the average lookahead times in different charging scenarios required for the employee driving profiles from the German mobility panel. Even in the most conservative scenario (charging at home with 3.7 kW), average lookahead times stay well below one day confirming the applicability of the ALAP approach. Furthermore, the analysis reveals that EV driving flexibility is to a great extent governed by the spatial availability of charging services and to a lesser extent by the charging speed. This is a valuable insight for more efficient planning of charging infrastructure investments.

Figure 6.13 illustrates the development of battery SOC over time for a group of EVs using ALAP charging. One can see that this charging approach tends to maintain fairly low battery levels with charging occurring shortly before a trip. The spike

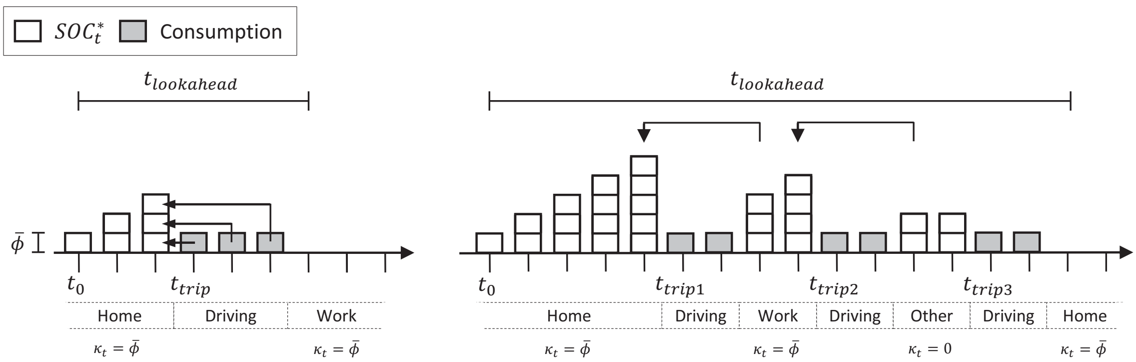


Figure 6.12: Determination of critical battery level SOC^*_t (For illustration purposes I simplify consumption per time slot to match $\bar{\phi}$.)

Table 6.4: Average (maximum) lookahead times in hours

	$\bar{\phi}$ [kW]							
Charging locations	3.7		7.4		11		22	
Home	6.8	(12.3)	6.1	(11.0)	5.9	(10.6)	5.7	(10.2)
Home and work	2.3	(6.8)	1.8	(5.7)	1.7	(5.4)	1.5	(5.0)
Home, work and other	1.1	(2.7)	0.7	(1.7)	0.6	(1.4)	0.5	(1.1)

on the right end of the interval is induced by an arbitrary full battery requirement at the end of the week.

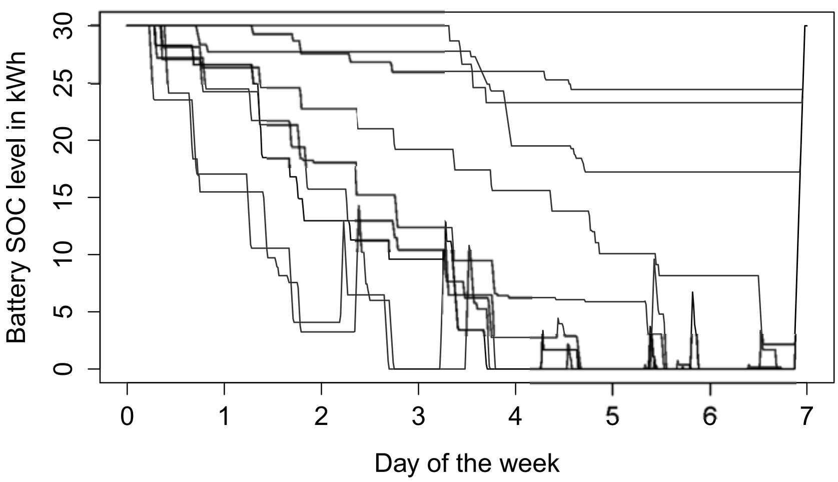


Figure 6.13: Battery level evolution of individual EVs under ALAP charging

Regular morning commutes lead to SOC_t^* typically inducing charging activity in the early morning/ late night (see Figure 6.1). Together with prevailing low night-time prices in electricity markets, this may result in an average charging cost decrease when moving from AFAP to ALAP charging regime. I want to emphasize that ALAP charging does not internalize any economic incentives and as such it is not any smarter than AFAP charging.

6.5.2 Extensions of as Late as Possible Charging

Given its simple structure with sequential and independent decisions, the ALAP-heuristic can be invoked on a per time step base to sequentially obtain the individual charging decisions depending on currently available information. This structure facilitates extending the ALAP strategy by using appropriate thresholds which can incorporate the available information. For example, by using price information to modify the ALAP policy one can introduce an economic charging rationale. Therefore, the ALAP strategy provides a flexible basis for additional charging strategies. The remainder of this section illustrates a variety of such ALAP extensions that reflect price-conscious charging, minimum range concerns or battery health.

As Late as Possible Charging with Price Thresholds

While the ALAP strategy does not respond to economic incentives it can easily be adapted to do so. Charging as late as possible offers the opportunity to observe current prices and use these observations to improve its charging costs. One can formulate a As Late As Possible Charging Strategy with price threshold (ALAP+) that induces charging when electricity prices are below a certain price threshold $\underline{c}$ or if the battery level is below SOC_t^*:

$$\phi_t^{ALAP+} = \begin{cases} \min\{\kappa_t, \overline{SOC} - SOC_t\} & \text{if } c_t < \underline{c}, \\ \max\{0, SOC_t^* - SOC_t\} & \text{otherwise.} \end{cases} \tag{6.15}$$

The threshold $\underline{c}$ can be adapted to a driver's driving behavior in order to further improve the effectiveness of the strategy. To determine a meaningful threshold level some basic statistical information (e.g., distributional properties such as mean or median of the electricity prices) is helpful. While this price threshold is ideally derived for each EV individually, I assume for ease of exposition a population-wide price threshold specified as a quantile of a given week's price distribution.

As Late as Possible Charging with Battery Threshold

ALAP charging clearly yields minimum EV availability and spontaneous range. By introducing a minimum battery level $\underline{\text{SOC}}$ that will trigger charging activity one can, as under optimal smart charging with thresholds, avoid this problem. Charging amounts of such ALAP-min charging then obtain as

$$\phi_t^{ALAP-min} = \begin{cases} \min\{\kappa_t, \overline{SOC} - SOC_t\} & \text{if } SOC_t < \underline{SOC}, \\ \max\{0, SOC_t^* - SOC_t\} & \text{otherwise.} \end{cases} \tag{6.16}$$

The introduction of minimum battery levels within the ALAP regime yields charging behavior resembling either AFAP charging, whenever $\underline{SOC}$ is binding ($SOC_t^* < SOC_t < \underline{SOC}$), or ALAP charging if $\underline{SOC} < SOC_t < SOC_t^*$.

Combined Heuristic Charging

By including both the price threshold $\underline{p}$ as well as the minimum battery level $\underline{SOC}$ into the basic ALAP strategy one obtains a heuristic smart charging strategy which responds to monetary incentives while at the same time incorporating minimum range levels. This represents EV charging behavior that reflects both economic and behavioral motives and still requires only very limited information on future trips and charging costs. Charging amounts of the heuristic are obtained as

$$\phi_t^{HEUR} = \begin{cases} \min\{\kappa_t, \overline{SOC} - SOC_t\} & \text{if } SOC_t < \underline{SOC} \vee c_t < \underline{c}, \\ \max\{0, SOC_t^* - SOC_t\} & \text{otherwise.} \end{cases} \tag{6.17}$$

This heuristic charging strategy can serve as a representation of EV charging loads for simulation models investigating charging loads. It can also provide a robust and simple planning logic for decision support systems aiming to improve charging costs based on limited user inputs.

Figure 6.14 provides individual charging cost comparisons for different weeks. As would be expected the results are somewhat in between optimal smart and AFAP charging: Both general cost levels and skewness are lower than under AFAP charging (Figure 6.7) and higher than under optimal smart charging (Figure 6.8).

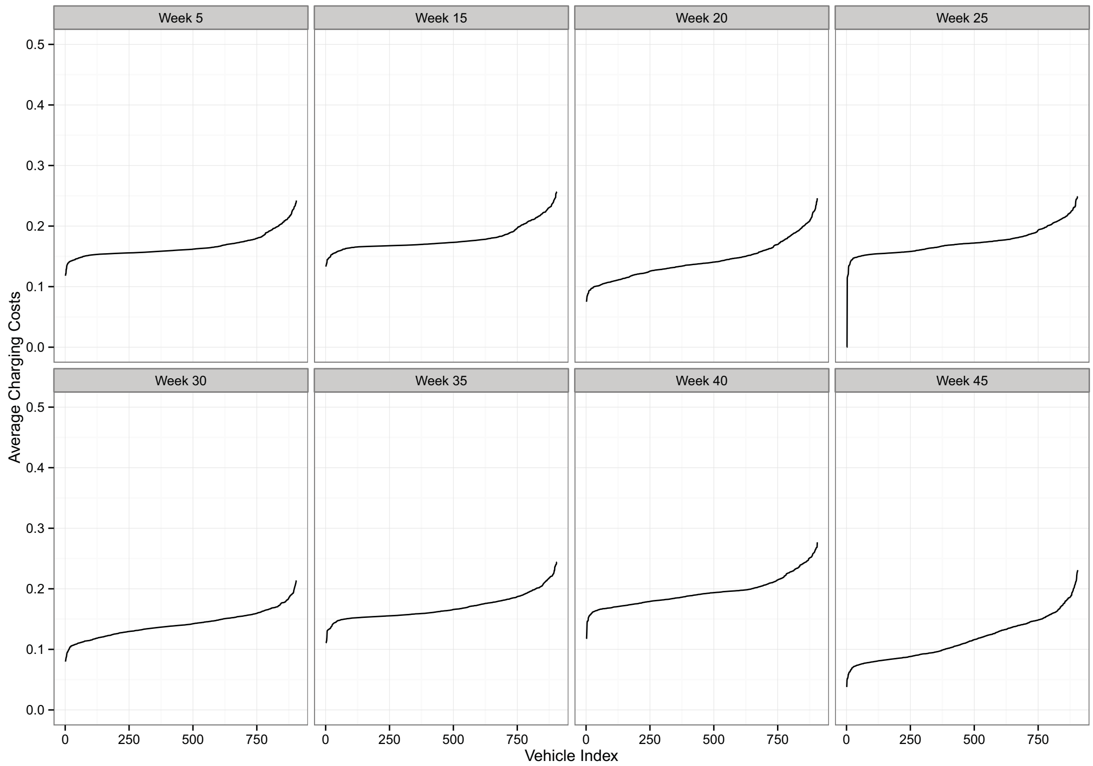


Figure 6.14: Comparison of average heuristic charging costs ($\underline{p} = 0.3, \underline{SOC} = 0.3$

As Late as Possible Charging with Full Price Knowledge

An interesting variant of the ALAP strategy is obtained under the knowledge of future prices. With knowledge of the next departure and the price path over the immediate future, one can derive an optimal short-term charging schedule for a given EV. Note that this approach is a combination of optimal smart charging and ALAP charging. Hence one can either formulate this strategy as a collection of full-information optimization problems with each having a limited horizon or as a threshold strategy.

The optimization problem is obtained by adopting Equations (6.2 – 6.7) to the shorter time frame and the threshold strategy readily obtains given the ALAP preprocessing (Figure 6.12): Let t_{trip} be the time of the next departure and $SOC^*_{t_{trip}}$ the corresponding critical battery level to be able to start this trip as provided by Algorithm 6.1. Then,

$$T_{ALAP} = \left[t..t_{trip} - 1\right]$$

is the set of time slots available for charging until departure and

$$SOC_{missing} = \max\left\{0, SOC^*_{t_{trip}} - SOC_t\right\}$$

the charging amount to be obtained over this period. It is easily verified that a bang-bang strategy, where charging occurs at the maximum admissible speed in the lowest cost time slots, is optimal in this setting. Sorting T_{ALAP} by increasing charging costs p_t one obtains T^{sorted}_{ALAP}. Let $\lfloor x \rfloor$ be the floor operator which returns the largest integer less or equal than x. Then the number of full charge time slots τ is given by

$$\tau = \left\lfloor \frac{SOC_{missing}}{\bar{\phi}} \right\rfloor. \tag{6.18}$$

The optimal[18] charging policy is then characterized as follows: Charge at $\bar{\phi}$ in the first τ time slots in T^{sorted}_{ALAP}, charge at $SOC_{missing} - \tau\bar{\phi}$ in the $\tau + 1$-th time slot. Considering the charging price in $\tau + 1$ as a threshold $\underline{c}' = c_{\tau+1}$ yields a more compact representation,

$$\phi_t^{ALAP-OPT} = \begin{cases} \bar{\phi} & \text{if } c_t < \underline{c}', \\ SOC_{missing} - \tau\bar{\phi} & \text{if } c_t = \underline{c}', \\ 0 & \text{otherwise.} \end{cases} \tag{6.19}$$

Note that Equation 6.19 structurally differs from Equation 6.15 as it incorporates the additional information encapsulated in $SOC_{missing}$ and τ. Furthermore, it should be emphasized that the extent of "perfect price knowledge" required for Optimal As Late As Possible Charging Strategy (ALAP-OPT) is governed by the look-ahead time as reported in Table 6.4. Consequently, it is still fairly limited price knowledge compared to the extent of information available in optimal smart charging scenarios.[19]

Uniform ALAP Charging

In its standard form as defined in Algorithm 6.1 population-wide ALAP charging yields load clustering prior to typical departure times (i.e. in the morning). These are the converse of evening load clusters exhibited in population-wide AFAP charging. From Equation (6.14) it is furthermore clear that EV agents will adapt a "bang-bang" charging scheme with either full or zero charging intensity. Considering battery and other component health such extreme charging patterns are especially problematic (Bashash et al., 2011). A smoother charging pattern with lower maximum power levels is thus to be preferred. One can modify the ALAP charging approach to minimize this effect by establishing a "uniform ALAP" procedure. Under this strategy the charge amount required at departure is *uniformly* allocated across all preceding time slots with charging possibility. Algorithm 6.2 allows determina-

[18] Optimality with respect to the limited planning horizon setting.

[19] In analogy to Section 6.4.1 one could also consider ALAP-OPT charging with backcast/ imperfect price forecasts but the additional insights would be limited.

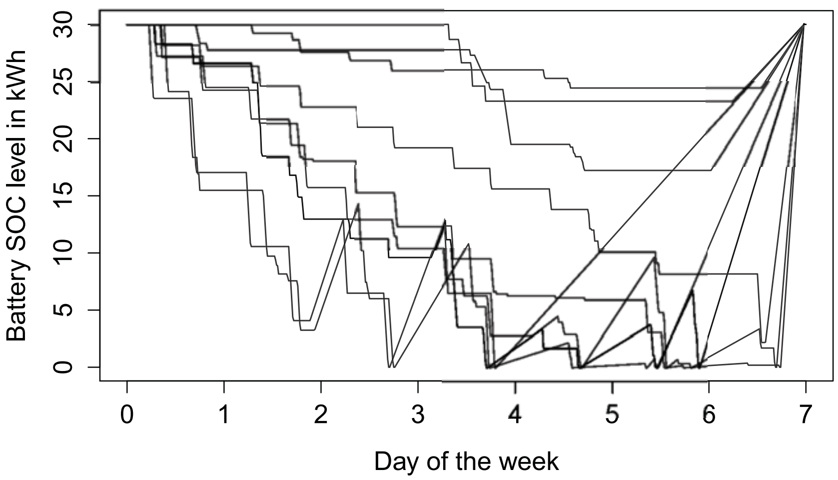


Figure 6.15: SOC level evolution of individual EVs under uniform ALAP charging

tion of the critical SOC for uniform ALAP charging. The charging decision is then analogue to Equation (6.14) using the updated critical SOC levels.

Algorithm 6.2 Critical SOC determination for uniform ALAP charging

---

$SOC^*_T = 0$
for $t = T$ to 1 **do**
  if $\gamma_t > 0$ **then**
    $SOC^*_{t-1} = SOC^*_t + \gamma_t$
  else if $\kappa_t = 0$ **then**
    $SOC^*_{t-1} = SOC^*_t$
  else
    $SOC^{req} = SOC^*_t$
    $\xi = t$
    while $\kappa_\xi > 0$ **do**
      $\xi = t - 1$
    for $\psi = t$ to ξ **do**
      $SOC^*_{\psi-1} = SOC^*_\psi - \frac{SOC^{req}}{\xi - t}$
    $t = \xi - 1$

Figure 6.15 illustrates the evolution of individual battery levels of selected driving profiles under uniform ALAP charging. In comparison with Figure 6.13, one can clearly see that charging occurs in a much more homogenous way (gentle slope of SOC curve as compared to near-vertical segments). This indicates that the availability of high charging speeds is not necessarily fully exploited and primarily serves as a "flexibility reserve" (cf. Table 6.4).

6.6 Categorization of Economic Charging Strategies

I have conceptualized the notion of economic charging strategies to characterize individual charging decisions which internalize monetary incentives as well as behavioral constraints. Besides these output-oriented criteria (characterizing the properties of the charging policy obtained), I also addressed different information regimes concerning required input information to formulate strategies. Using these information requirements one can identify different regimes that span distinct smart charging paradigms which EV decision support can address. Figure 6.16 summarizes these findings by creating a taxonomy of the aforementioned charging strategies spanned by informational requirements concerning future prices[20] and upcoming trips. In addition to the well-established corner cases optimal smart and simple AFAP charging, it also bridges the intermediate in-between areas. This is due to the novel heuristic charging strategies and modified optimization approaches which are able to internalize limited information regimes while still internalizing economic incentives.

A special remark concerns the upper right cases where no trip information is available: Following Proposition 6.2, in situations without any information on future trips the only applicable charging strategy is the AFAP strategy as otherwise vehicle availability is no longer guaranteed. In the absence of price information (bottom row) one cannot formulate a meaningful objective and are hence restricted to non-economic charging strategies. Depending on the available trip information these are the AFAP, (uniform) ALAP and the minimization of maximum charging power.

Price Information \ Trip Information	Full	Limited	None
Full	Optimal	ALAP-OPT	n/a
Limited	Backcast Optimal Charging	ALAP+, HEUR	n/a
None	Minimal Maximum Charge Power	ALAP, Uniform ALAP, ALAP-min	AFAP

Figure 6.16: Taxonomy of Economic Charging Strategies (Flath et al., 2012)

[20] As mentioned in Section 6.4.2, price information can be substituted for other temporal optimization criteria.

6.7 Comparisons and Evaluation Results

To illustrate and compare the different charging strategies discussed above, I analyze selected evaluation criteria concerning charging costs and driving flexibility for different charging scenarios (charging speed and charging location). As described in Section 6.1.6, the following results obtain from an annual analysis using 2010 EPEX spot prices and looping the weekly driving profiles. Evaluation results are presented in Table 6.5 and discussed in the remainder of this Section.

6.7.1 Vehicle Availability Levels

With range anxiety being a central obstacle to widespread adoption of electric vehicles I want to specifically look into the vehicle availability levels achieved under the different charging regimes. The average SOC level over all vehicles and all time slots provides a good indication as it effectively measures available spontaneous range.

AFAP charging ensures average SOC levels well above 95% which once more indicates that the EV specification chosen in Section 6.1.5 provides ample range to fulfill employee driving profiles. Here, average battery levels are increasing in charging speed as vehicle range is more quickly restored upon connection of the charger. On the other hand, ALAP establishes the minimum average battery level and exhibits average battery levels decreasing in charging power as charging will start even later. The gap of around 90% between AFAP and ALAP battery levels indicates that there is significant load flexibility in pursuing these very different charging programs. Battery-conscious uniform ALAP charging somewhat increases average battery levels. However, both ALAP regimes will skip initial charging opportunities and subsequently remain at very low SOC levels. This becomes evident given the comparison with minimum MaxLoad charging which optimally distributes charging activity and is thus similar in spirit to uniform ALAP charging. This approach yields average battery levels of 55%. Introducing price and battery thresholds to ALAP charging greatly increases the average SOC. One can make an analogue observation for optimal smart charging which exhibits average battery levels around 54% to 62% in the standard form without minimum battery level. These levels correspondingly increase to 62% to 68% (72% to 76%) when introducing a minimum SOC level of 25% (50%) as described in Section 6.4.1.

6.7.2 Charging Costs

Achieving an improved demand-supply-matching is the key motivation behind price-based charging coordination and lower average charging costs are thus an indication of charging strategies internalizing load shifting incentives and the adaptability to a given price regime. Average charging costs under AFAP charging exceed the average electricity price of 0.237 €/kWh (as obtained from the scaled and interpolated EPEX spot price as mentioned in Section 6.2). Therefore, AFAP charging mostly occurs during times of increased system load. ALAP charging achieves minimally lower charging costs than AFAP but still exceeds the average price. The

Table 6.5: Cost and driving flexibility evaluation of different charging strategies ($SOC_0 = SOC_T = 0.5$; for AFAP SOC_T will typically be higher)

			Home & Work				Only at Home	
			3.7 kW	7.4 kW	11 kW	22 kW	7.4 kW	11 kW
AFAP	Avg. costs	$[\frac{€}{kWh}]$	0.266	0.270	0.271	0.272	0.262	0.264
	Avg. SOC	[pct.]	98.4%	98.8%	98.9%	99.0%	96.7%	96.8%
ALAP	Avg. costs	$[\frac{€}{kWh}]$	0.262	0.267	0.264	0.270	0.258	0.264
	Avg. SOC	[pct.]	4.4%	4.1%	6.1%	3.9%	6.3%	6.1%
Uniform ALAP	Avg. costs	$[\frac{€}{kWh}]$	0.230	0.231	0.231	0.231	0.216	0.216
	Avg. SOC	[pct.]	26.6%	26.3%	26.2%	26.2%	27.9%	27.8%
Min MaxLoad	Avg. costs	$[\frac{€}{kWh}]$	0.233	0.233	0.233	0.233	0.216	0.216
	Avg. SOC	[pct.]	56.9%	56.9%	56.9%	56.9%	55.3%	55.3%
ALAP-HEUR	Avg. costs	$[\frac{€}{kWh}]$	0.178	0.185	0.189	0.193	0.185	0.189
$\underline{SOC} = 0.3$, $\underline{c} = 0.3$	Avg. SOC	[pct.]	91.3%	92.6%	92.9%	93.1%	92.5%	92.7%
ALAP-HEUR	Avg. costs	$[\frac{€}{kWh}]$	0.159	0.156	0.158	0.16	0.155	0.160
$\underline{SOC} = 0.25$, $\underline{c} = 0.1$	Avg. SOC	[pct.]	74.6%	78.9%	80.2%	81.3%	78.8%	81.3%
ALAP-HEUR	Avg. costs	$[\frac{€}{kWh}]$	0.169	0.157	0.155	0.155	0.154	0.154
$\underline{SOC} = 0.15$, $\underline{c} = 0.05$	Avg. SOC	[pct.]	59.8%	66.7%	68.7%	70.8%	66.8%	68.8%
ALAP-OPT	Avg. costs	$[\frac{€}{kWh}]$	0.180	0.176	0.175	0.176	0.152	0.151
	Avg. SOC	[pct.]	24.9 %	24.8 %	24.8%	24.9%	26.3%	26.3%
OPT-backcast	Avg. costs	$[\frac{€}{kWh}]$	0.145	0.140	0.139	0.137	0.140	0.138
	Avg. SOC	[pct.]	53.9%	56.5%	59.0%	62.0%	56.3%	58.8%
OPT-minSOC 50%	Avg. costs	$[\frac{€}{kWh}]$	0.141	0.133	0.131	0.129	0.134	0.132
	Avg. SOC	[pct.]	72.4%	73.5%	74.4%	76.0%	73.4%	74.3%
OPT-minSOC 25%	Avg. costs	$[\frac{€}{kWh}]$	0.126	0.115	0.111	0.108	0.116	0.101
	Avg. SOC	[pct.]	62.2%	65.5%	66.1%	67.7%	65.4%	59.1%
OPT	Avg. costs	$[\frac{€}{kWh}]$	0.117	0.106	0.101	0.096	0.106	0.101
	Avg. SOC	[pct.]	54.3%	57.0%	59.2%	62.0%	56.9%	59.1%

results are not too surprising as both strategies do not internalize economic incentives. Uniform ALAP spreads charging activity across available time windows and this way secures cost improvements at night over the other two charging strategies. Minimum MaxLoad charging yields almost identical charging costs which furthermore confirms that the two strategies yield very similar charging patterns.

On the other hand, cost-aware charging protocols achieve significant cost savings. This is true for both optimal and heuristic smart charging. For optimal smart charging average charging costs are decreasing in charging speeds as low price periods (e.g., availability of electricity from renewable sources) can be used more effectively. Interestingly, the same is not necessarily true under heuristic charging — without perfect price knowledge the reactivity to an à priori unknown price signals cannot always be fully eploited.

This observation is confirmed by the cost results achieved by ALAP charging with full price knowledge which are decreasing in charging power. ALAP-OPT charging achieves lower costs when charging is restricted to homes. This is because the critical SOC level is determined on a per-trip basis factoring in the next charging possibility (see Figure 6.12). If charging is possible at work the energy required for the trip home will be charged during work hours which coincide with higher EPEX prices. Still, heuristic smart charging achieves greatly reduced charging costs over AFAP charging as well as the average EPEX spot price. By adjusting the two thresholds one can moderate between cost optimization (charging costs) and range anxiety (average SOC).

6.7.3 Cost of Availability

By comparing the optimal smart charging results with the optimal results in the presence of minimum SOC levels one obtains an indication of the cost of ensuring these vehicle service levels. Considering the small cost gap per kWh (about one cent for 25%, about three cents for 50%) compared with non-constrained optimal smart charging one can infer that smart charging is still very effective even in the presence of minimum SOC constraints. This confirms the initial observation of similar charging patterns from Figure 6.9.

For a closer analysis, I look at Figure 6.17. Note that a minimum SOC level of 100% would intuitively reduce smart charging to AFAP charging. However, given the relaxed formulation of the minimum SOC charging condition in Equation (6.8) the optimization can still improve on plain AFAP charging.[21] Clearly, this is good news as it means that addressing the omni-present range anxiety impairs economic charging coordination only too a limited extent.

6.7.4 Price vs. Trip Information

Considering the overview of strategies from Figure 6.16, it is of special interest to compare the relative importance of the different information regimes — trip and

[21]The average SOC level of 97.9% is consequently also lower than the value of 98.9% obtained under AFAP charging.

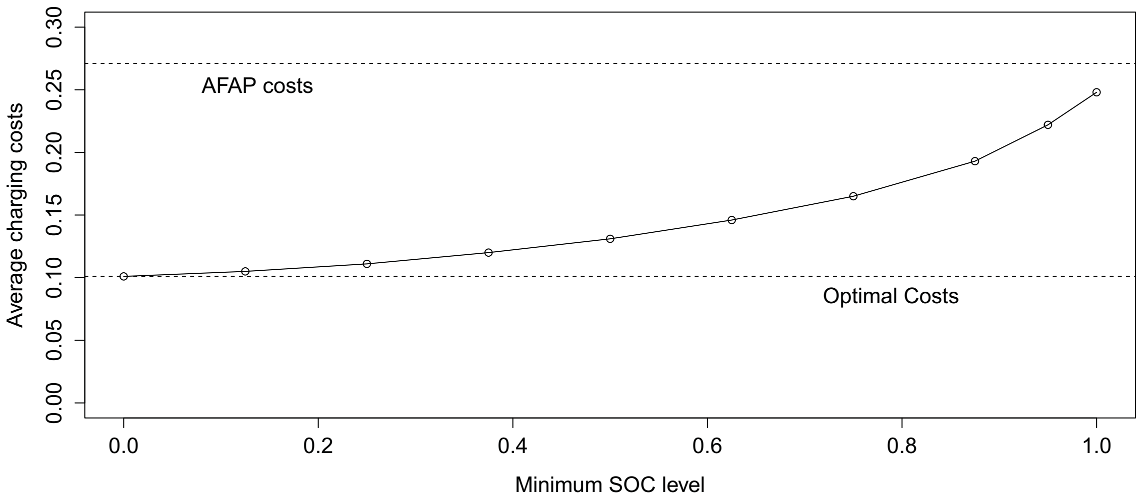


Figure 6.17: Average charging costs for different minimum SOC levels (11kW, $SOC_0 = SOC_T = 0.5$)

price information. The low cost of availability as discussed provides a first indication as this range buffer is applied for unplanned trips, i.e. situations of limited information on future trips. To further analyze this question I benchmark the charging costs achieved under ALAP-OPT charging (with full price information) against the costs obtained under optimal smart charging with backcast prices. While one does know that

$$\sum_{t=1}^{T}\left(c_t \cdot \phi_t^{OPT}\right) \leq \sum_{t=1}^{T}\left(c_t \cdot \phi_t^{OPT-BACK}\right),$$

and

$$\sum_{t=1}^{T}\left(c_t \cdot \phi_t^{OPT}\right) \leq \sum_{t=1}^{T}\left(c_t \cdot \phi_t^{ALAP-OPT}\right),$$

the ranking of ALAP-OPT against smart charging with backcast prices is ambiguous. I focus on the charging at home cases as otherwise ALAP-OPT would perform significantly worse due to charging at the workplace at typically elevated prices. The results suggest that trip information is more valuable than price information. This makes intuitive sense since certain price patterns are not too surprising (e.g., low weekend prices) and backcast optimal charging can leverage these by postponing charging activity. On the other hand, ALAP-OPT can only optimize charging activity for each upcoming trip segment which prevents “saving” up. This is even more evident when comparing the minimal charging cost differential between ALAP-OPT and heuristic smart charging with aggressive price thresholds: The latter has very limited information and still achieves reasonably low charging costs. Therefore, I argue that trip information is of greater relative importance compared to price information. This is especially true when taking into account forecast prices as discussed in Section 6.4.1. These results indicate that preference elicitation, decision support and incentive design for EV charging services should especially emphasize the value of trip information.

6.8 Discussion

Growing numbers of electric vehicles present both a challenge (large loads) and an opportunity (charging flexibility can be used for DSM) to the electricity grid. Therefore, charging loads and flexibility need to be assessed to evaluate the EV grid impact and to subsequently develop robust coordination procedures. Due to a very limited number of currently active EV, appropriate models are essential in addressing this task. This chapter applied the customer modeling framework to develop EV models reflecting technical characteristics, driving behavior and charging strategies. Fundamentally, smart EV charging is about handling the trade-off between range management and optimized charging schedules with respect to cost, emissions or battery health. Depending on the quality of price and trip information, different charging strategies can be determined. The evaluation results suggest that trip information may be more important than price information.

6.8.1 Limitations

Sparse data on EV technical specifications and the lack of comprehensive mobility data based on actual EV present challenges to appropriate calibration of EV models. While the presented workarounds using synthetic EV driving profiles and generic EV technology parameters are sound and well-established in research, they may still somewhat limit the generalizations of the obtained results. Similarly, the assumed linear charging model simplifies real-world battery management procedures. Moreover, the presented analysis does not consider Vehicle-to-Grid (V2G) scenarios as proposed by Kempton and Letendre (1997). However, both optimal and heuristic smart charging are readily adapted to include feeding back electricity to the grid.

6.8.2 Beyond Charging Strategies

The key motivation behind extending the charging strategy space towards less information-reliant heuristic strategies is the uncertainty inherent to the electricity prices and mobility behavior. I especially argued that one cannot formulate sophisticated — i.e. improving on plain AFAP — charging strategies without trip information (Proposition 6.2). Static charging strategies provide a proper means to describe economic charging behavior in sufficiently stable settings with respect to prices and mobility behavior. To be precise, this setting corresponds to traditional scenarios where the mode of transportation is fixed and pricing is handled through a, potentially variable, posted price per kWh of electricity. On the other hand, future scenarios of integrated mobility services, more volatile electricity prices and complex rate greements may not comport with these requirements: Drivers may become more flexible concerning their mode of transportation, switching regularly between EV and other mobility options. Similarly, electricity rates are envisioned to evolve into a more market-style system where prices obtain from dynamic local matching of generation and demand.

Trip-level Valuation

To ensure comparability across the different charging strategies, completion of all trips specified in the driving profile was a central requirement in the sections before. However, in an integrated system of mobility services, customers may potentially be willing to forfeit a car trip and take an alternative means of transportation (e.g., car- and ride-sharing or public transportation). Capturing this type of flexibility requires an appropriate representation of the costs and benefits of different mobility modes. These costs can be direct, e.g., fuel costs (Gerding et al., 2011), or indirect, e.g., disutility from waiting or transportation mode changes (Domencich and McFadden, 1975). Furthermore, dynamic aspects such as risks of delay (Tseng, 2008), trip scheduling (Small, 1982; Hendrickson and Plank, 1984) and the value of individual flexibility (Bertolini and Le Clercq, 2003) need to be represented.

Within such a more comprehensive model, one can analyze EV charging behavior in the context of multi-modal mobility chains. Consequently, the extent of EV usage will be endogenous in contrast to rigid driving profile models: High charging costs result in EV usage being reduced while low charging costs may increase the number of EV trips. Clearly, static optimization approaches are likely to fail in such richer settings. Therefore, alternative approaches for smart charging like heuristics or learning models are required.

Learning-based Electric Vehicle Charging Behavior

Dauer et al. (2013) propose a learning approach that endogenizes the fundamental charging trade-off between range and flexibility on the one hand, versus charging costs on the other. They formulate an appropriate learning approach which is capable to determine the value of charging for different range-availability states. Denoting the trip time by T, these states are bounded from below by SOC_t^* for all $t < T$, and from above by SOC_T^*. Figure 6.18 illustrates this state representation. Clearly, these states implicitly wrap different levels of charging urgency which the EV charging behavior needs to internalize.

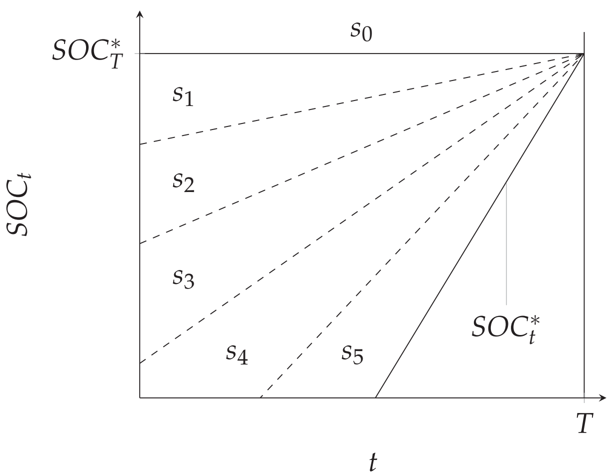


Figure 6.18: State Space for Electric Vehicle Learning (Dauer et al., 2013)

Charging Markets

A very direct implementation of the cost-availability trade-off is the establishment of charging markets where EV agents post bids for limited charging capacity. Clearly, engaging in such a charging market requires EV agents to formulate an appropriate bidding strategy (Ramchurn et al., 2012). Considering the fundamental trade-off in economic charging behavior between range and flexibility on the one hand versus charging costs on the other, an appropriate learning approach will have to endogenously determine the value of given SOC levels. Requiring a high flexibility level (equivalent to AFAP charging) means submitting relatively high bids to be allocated sufficient charging capacity. Conversely, cost-sensitive bidding behavior could yield lower vehicle service levels with insufficient SOC levels for certain trips. Provided with an appropriate valuation for vehicle availability a sophisticated learning environment can translate this trade-off into appropriate bidding behavior taking into account market behavior, personal driving habits and current vehicle status.

Battery Change

While most car manufacturers focus on EV-internal charging solutions, the Better Place project[22] pursues a combined approach of EV charging and battery switching. This battery swap offers drivers the possibility to automatically exchange the battery in battery switch stations. The battery swap service allows customers to instantaneously restore their vehicle range (Agassi, 2009) and solves some major problems of EVs: For one, batteries can be charged in a more controlled manner within the charging station due to a smoother charging schedule (Wang et al., 2011). Secondly, drivers' range anxiety is greatly reduced. Furthermore, exchangeable batteries increase the reliability of EVs and avoid the risk of decreasing battery performance or even defects. Given the high cost of batteries the number of replacement batteries are a critical cost factor for the realization of this business models. One can adopt the model framework used to describe EV charging behavior to include this battery swap activity. Such an analysis offers insights on vehicle availability levels, spare battery requirements as well as charging flexibility within battery change systems.

[22] `www.betterplace.com`

Chapter 7

EV Charging Coordination

Individual charging behavior of EV agents ultimately governs both vehicle-level availability and cost levels as well as the emergent population behavior (Ramchurn et al., 2012). In the scope of this work, this essentially means determining aggregate behavior of a given set of loads, in this case the total load resulting from the charging activity of a population of EVs $i \in [1..n]$. Focusing on load matching objectives (i.e. ignoring transmission or power flow constraints), charging load aggregation only requires summing individual charging decisions (or respectively discharging decisions with negative sign, in the case of V2G scenarios) across the vehicle population, $\Phi_t = \sum_{i=0}^{n} \phi_t^i$. Depending on the analysis scenario, the concrete implementation setting choice will differ with respect to the available information set, decision model and potential agent interactions due to coordination mechanisms.

Leveraging the two population modeling paradigms discussed in Chapter 3, this chapter presents both bottom-up and top-down approaches to analyze EV charging load coordination. The first section uses a bottom-up model approach based on the EV charging model introduced in previous chapter. Using appropriate aggregation schemes, the emergent population charging load is analyzed for alternative incentive scenarios. Subsequently, a top-down approach for EV population charging behavior is developed. This is used to develop and evaluate a capacity-based charging coordination approach based on the Perishable Asset Revenue Management (PARM) literature.[1]

7.1 Bottom-up Population Model

Individual EV models as described in the previous chapter can easily be applied to describe an EV population using a proper aggregation scheme. By postulating a certain locational clustering (see Section 6.1.3), charging loads can be aligned spatially. The identical time base of the driving profiles, furthermore, facilitates temporal alignment. However, one needs to characterize sequential versus parallel decision-making when analyzing coordination approaches. In the following I first

[1] The material in this chapter was in parts previously presented within Flath et al. (2012) and Flath et al. (2013).

look at the aggregate loads obtained under uncoordinated charging. Subsequently, I look at aggregate load under exogenous (no feedback-loop) and endogenous (with feedback-loop) coordination mechanisms and discuss the required changes to the aggregation scheme.

Building on the results from the previous chapter, all analyses and results reported in this chapter utilize the same base population of 907 driving profiles. Clearly, this is an illustrative choice and the approaches are easily adapted to more explicitly specified contexts, e.g., a concrete distribution grid scenario.

7.1.1 Aggregate Load Without Charging Coordination

In the absence of charging coordination mechanisms (e.g., linear pricing), EV drivers will either adopt AFAP charging behavior to maximize vehicle availability or they will opt for maximizing battery health by minimizing the maximum charging power. In both cases individual EV agents formulate their policies independent of price information, the system state or the actions of other EVs. Under these premises, emergent population behavior can be replicated by aggregating charging decisions of individual EVs as shown in Figure 7.1.

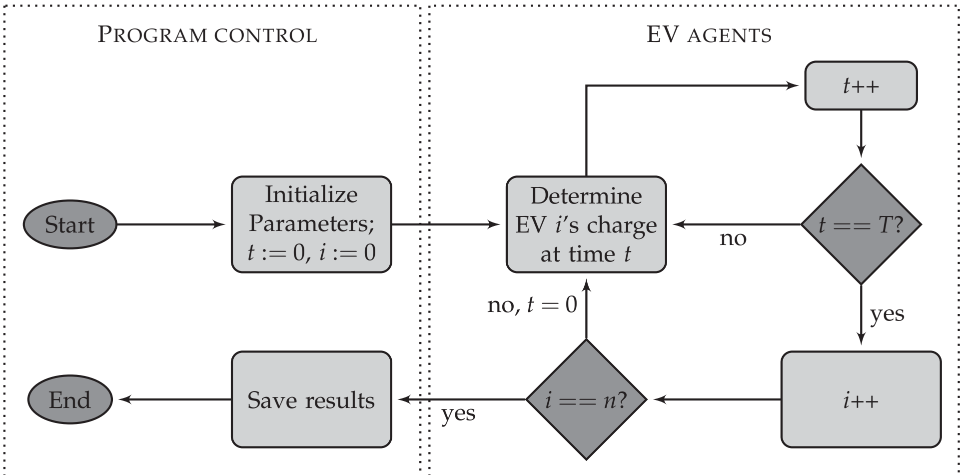


Figure 7.1: Model work flow for bottom-up population model without coordination

AFAP Charging Population

Figure 7.2 depicts the aggregate load pattern obtained under population-wide AFAP charging. This aggregate load pattern tracks the commuter mobility behavior with load clustering occurring at the *Work* location in the morning and at *Home* in the evening. Due to the temporal heterogeneity in the driving profiles these clusterings are somewhat spread out. However, given the AFAP charging behavior with $\bar{\phi}$ charging, one can still observe distinct peaks.

Table 7.1 reports the average charging costs, the average SOC level, the share of overload situations assuming a 2,000 kW transformer and the maximum load level for different charging modes over 51 weeks. Concerning the coordination goals discussed in Section 2.2, the average charging costs are a proxy for load-generation matching while the maximum load as well as the overload share are measures for the grid impact.

Table 7.1: Aggregate impact of AFAP charging under different maximum charging speeds $\bar{\phi}$ on average costs, average SOC levels and load spikes. $SOC_{\text{init}} = 100\%$. Profiles infeasible at low charging power levels have been removed in the corresponding columns.

			$\bar{\phi}$ [kW]			
			3.7	7.4	11	22
AFAP	Avg. costs	[$\frac{€}{kWh}$]	0.266	0.270	0.271	0.271
$\underline{SOC} = 1.0$	Avg. SOC	[pct.]	98.4%	98.8%	98.9%	99.0%
	Overloads	[pct.]	0.0%	0.0%	0.0%	0.0%
	Max. Load	[kW]	589	709	740	838

Confirming prior research (e.g., Sioshansi, 2012), AFAP charging exhibits very limited load clustering with maximum load levels remaining well below 1,000 kW across all charging speed levels. This indicates that driving patterns are sufficiently heterogeneous to facilitate distributed charging behavior. Yet, average charging costs exceed the average electricity price of 0.237 €/kWh. Therefore, AFAP charging mostly occurs during times of higher than average system load.

Minimum MaxLoad Charging Population

One could already see in Figure 6.9 that EV mobility requirements can be met with fairly low maximum charging load levels. Consequently, population-wide adoption of such charging behavior yields even lower aggregate load levels than under AFAP charging (Figure 7.3). One can see that the charging pattern is spread out as much as possible, both at the *Home* and the *Work* location. Considering the results over time, Table 7.2 does not account for different $\bar{\phi}$ values as this quantity does not affect the optimal policy under minimum MaxLoad Charging.

Table 7.2: Aggregate impact of Min MaxLoad charging under different maximum charging speeds $\bar{\phi}$ on average costs, average SOC levels and load spikes. $SOC_{\text{init}} = 100\%$, $SOC_{\text{terminal}} = 50\%$.

Min MaxLoad	Avg. costs	[$\frac{€}{kWh}$]	0.233
$\underline{SOC} = 1.0$	Avg. SOC	[pct.]	56.9%
	Overloads	[pct.]	0.0%
	Max. Load	[kW]	227

The results over 51 weeks confirm the impression from Figure 7.3 with a total maximum load of 227 kW. Average charging costs are 0.233 €. This corresponds to the average EPEX spot price. This is hardly surprising as charging activity occurs very much distributed over all time intervals. As for AFAP charging, this especially means that aggregate charging is not necessarily aligned with system-wide availability of generation output.

In summary, while a "laissez-faire" approach to EV charging coordination shelters the grid from local overloads and load spikes, it is sub-optimal with respect to load-generation matching.

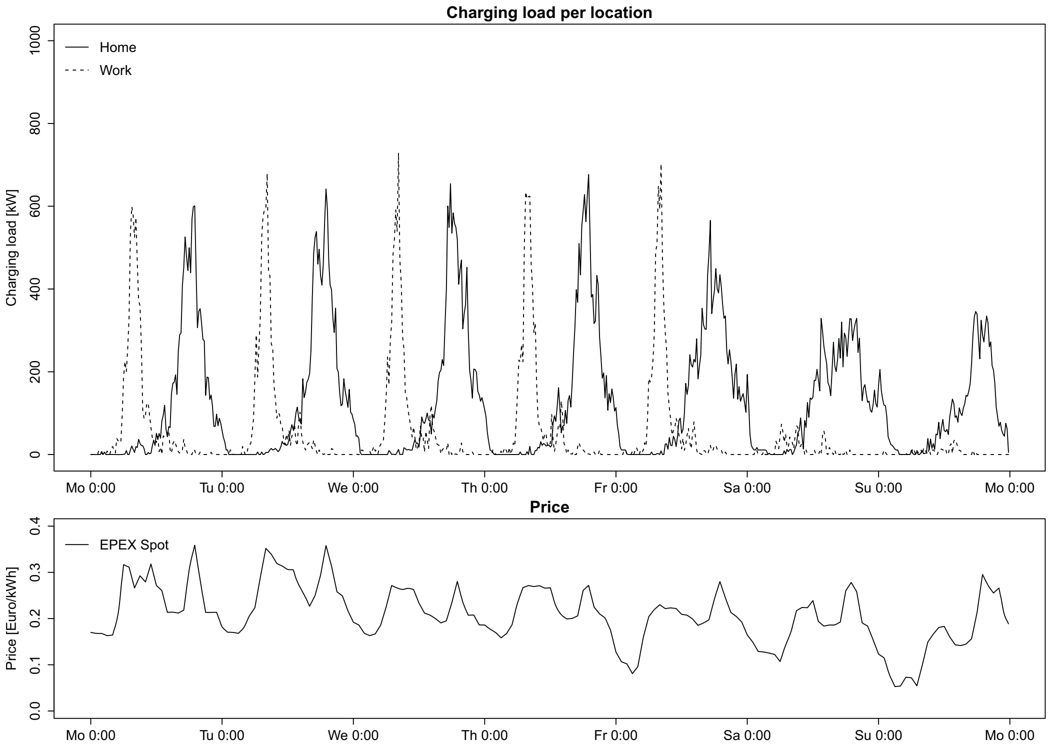


Figure 7.2: Aggregate load under AFAP charging ($\bar{\phi} = 11kW$, $SOC_0 = 100\%$)

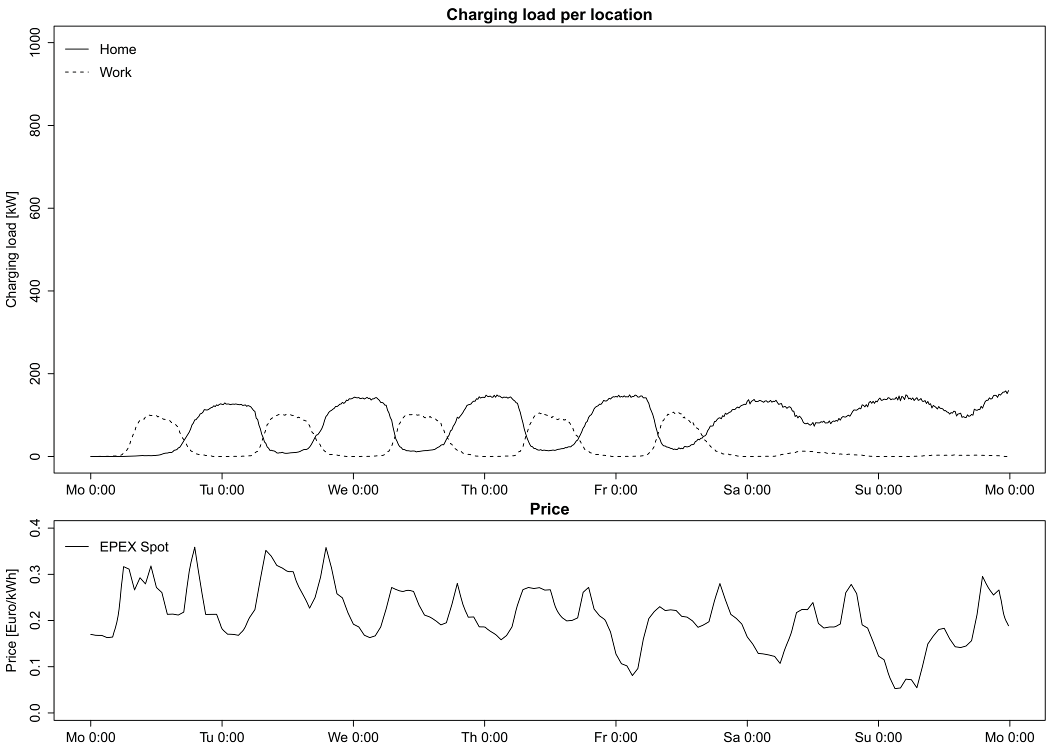


Figure 7.3: Aggregate load under minimal maximum load charging ($\bar{\phi} = 11kW$, $SOC_0 = 100\%$, $SOC_T = 50\%$)

7.1.2 Aggregate Load with Exogenous Charging Coordination

Given the importance of load-generation matching, an intuitive solution to achieve better charging coordination lies in using the exogenous wholesale electricity market price as a coordination objective for individual vehicles. This can be achieved by means of RTP or appropriate granular TOU rates. I want to analyze aggregate load under both optimal full-information and heuristic limited-information charging. For the latter, I fix $\underline{p}$ at the 0.3 quantile of the respective week and $\underline{SOC}$ to 30% of total battery capacity.

Under wholesale electricity price coordination one can find that aggregate load exhibits extreme spikes greatly exceeding 2,000 kW independent of the charging strategy (Figures 7.4 and 7.5). Such herding effects are in line with results from prior research on the effects of price-based coordination in retail electricity markets and EV charging scenarios (Rahman and Shrestha, 1993; Gottwalt et al., 2011; Sioshansi, 2012). Another striking observation is that, although charging is possible at both the *Home* and the *Work* location, hardly any charging activity occurs away from *Home*.

The reason for this load concentration is that low electricity prices typically coincide with night hours when private cars are parked at home. Consequently, pricing of EV charging services based on wholesale electricity prices will lead to both temporal *and* spatial clustering of charging activity. With increasing EV penetration, the stability of residential distribution grids may be significantly endangered.

Load Sensitivity to Charging Power

A key question arising from the significant load spikes observed on the aggregate population level is their sensitivity to different maximum charging power levels. Intuitively, curtailing maximum charge power limits the magnitude of load spikes for a given number of concurrent charge processes. Notably, by ensuring

$$n\bar{\phi} < \Phi^{lim} \Leftrightarrow \bar{\phi} < \frac{\Phi^{lim}}{n}$$

transformer overloads can be completely ruled out. While the magnitude of spikes is reduced, one can also intuit that longer charging times give rise to more temporal overlap in EVs' charging activity. Furthermore, low charging speeds also increase the planning horizon (see Table 6.4) and, moreover, 12 additional driving profiles become infeasible at the lowest charging power level. Thus, curtailing charging loads further limits EV flexibility and hence customer acceptance. Additionally, EVs cannot fully utilize low wholesale electricity prices under a low charging speed regime. This may prevent an efficient allocation of available renewable generation. Table 7.3 reports the population average charging costs, average battery SOC levels, the percentage of overloaded time slots and the maximum load level for different maximum charging power levels and charging strategies.

The results for optimal smart charging confirm the basic intuitions concerning charging speed variations: Average charging costs are decreasing with high charging speeds as low price periods (e.g., availability of electricity from renewable sources) can be used more effectively. By the same token, maximum load levels

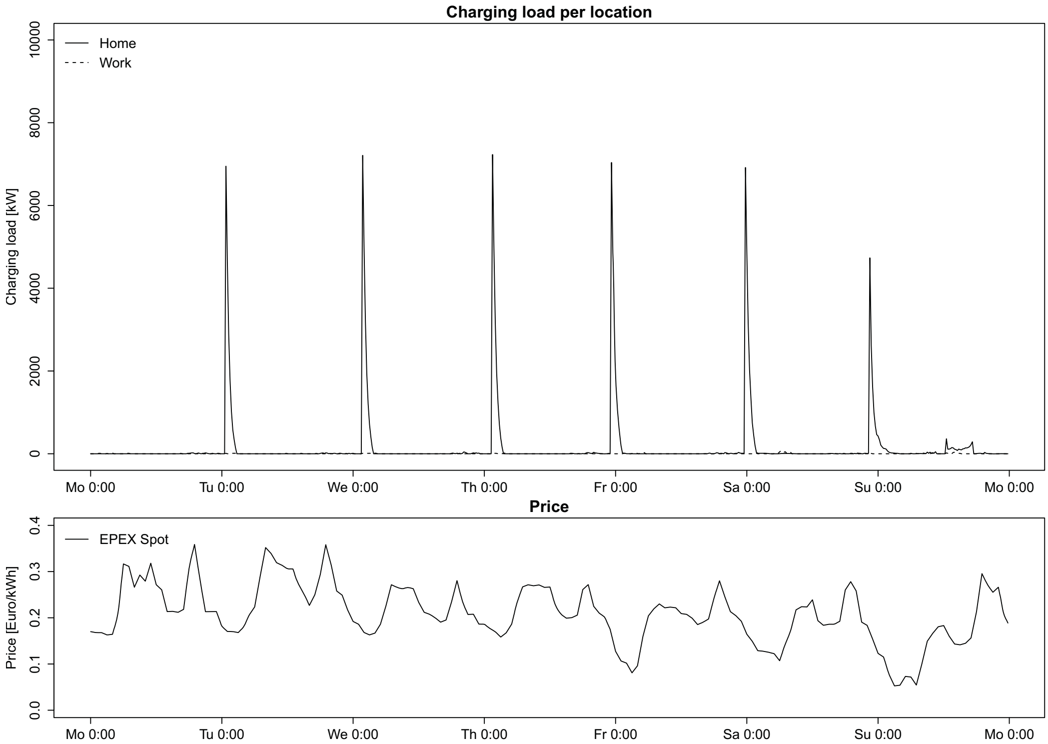


Figure 7.4: Aggregate Load under heuristic smart charging ($\bar{\phi} = 11kW$, $SOC_0 = 100\%$, $SOC_T = 90\%$, $\underline{p} = 0.3$)

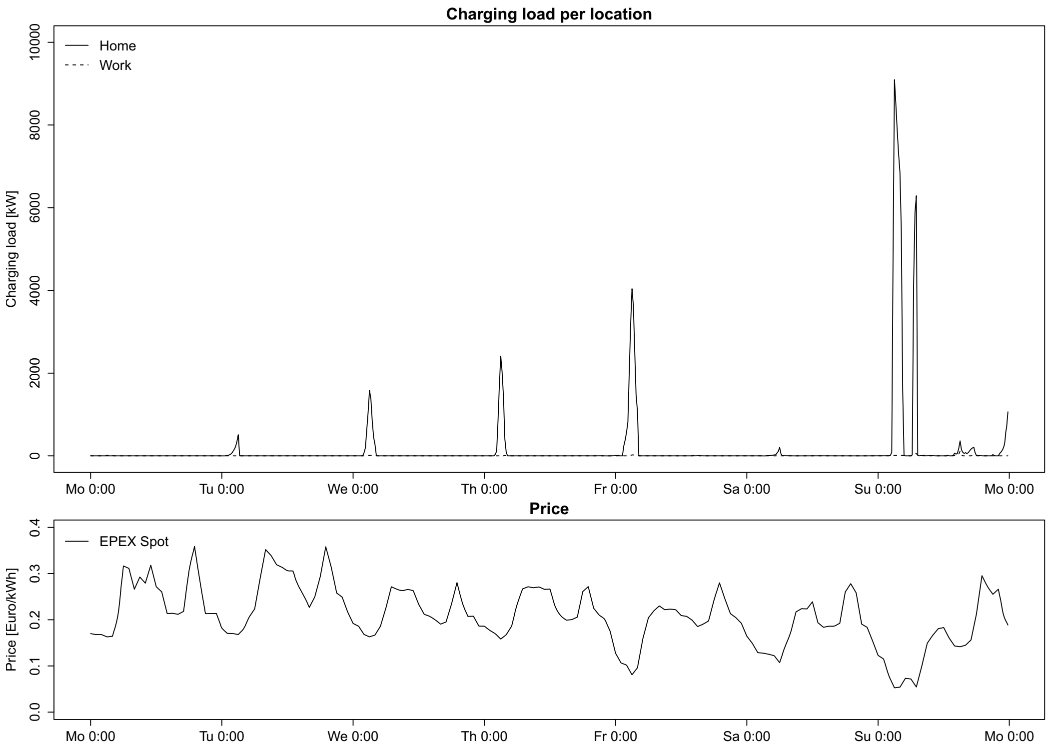


Figure 7.5: Aggregate Load under optimal smart charging ($\bar{\phi} = 11kW$, $SOC_0 = 100\%$, $SOC_T = 90\%$)

Table 7.3: Impact of maximum charging speed $\bar{\phi}$ and charging strategies on average costs, average SOC levels and load spikes. $SOC_{\text{init}} = 100\%$, $SOC_{\text{terminal}} = 90\%$. Profiles infeasible at low charging power levels have been removed in the corresponding columns.

			$\bar{\phi}$ [kW]			
			3.7	7.4	11	22
OPT	Avg. costs	$[\frac{€}{kWh}]$	0.119	0.107	0.102	0.097
	Avg. SOC	[pct.]	68.3%	68.1%	68.2%	68.8%
	Overloads	[pct.]	3.1%	3.2%	2.7%	2.0%
	Max. Load	[kW]	3,297	6,671	9,900	19,623
HEUR	Avg. costs	$[\frac{€}{kWh}]$	0.178	0.185	0.189	0.193
$\underline{SOC} = 0.3$	Avg. SOC	[pct.]	91.3%	92.6%	92.9%	93.1%
$\underline{p} = 0.3$	Overloads	[pct.]	2.3%	3.2%	2.9%	2.1%
	Max. Load	[kW]	2,977	5,802	8,388	15,357

(overload magnitude) greatly increase during these low price times while the absolute number of overloads decreases as charging occurs in fewer time slots. As before, it is tempting to assume that these extreme load levels are driven by the clairvoyant nature of optimal smart charging strategy. However, the heuristic smart charging results exhibit similar effects: Again, significant load spikes occur for all levels of $\bar{\phi}$ and the magnitude of these peaks is increasing in charging speed. Interestingly, while optimal charging costs are strictly lower for higher charging speed, the same is not necessarily true under heuristic charging — without perfect price knowledge the reactivity to a priori unknown price signals is less effective.[2] Still, heuristic smart charging achieves greatly reduced charging costs over AFAP charging as well as the average EPEX spot price. By adjusting the two thresholds one can moderate between cost optimization (charging costs) and range anxiety (average SOC).

Under both optimal and heuristic smart charging transformer overloads occur independent of the maximum charging power level. This indicates that coordination through exogenous price signals (e.g., a national wholesale price) is prone to over-coordination. Lower charging power levels help reduce the magnitude of load spikes but do not directly address the underlying problem of spatio-temporal clustering and limit EV availability. Ideally, one wants to mitigate spatial load clustering while retaining price responsiveness and EV flexibility. Exogenous coordination approaches without feedback-loop cannot avoid avalanche effects while uncoordinated charging does not achieve a sufficient load-generation matching. Therefore, I next consider an endogenous coordination approach with feedback-loop.

7.1.3 Aggregate Load with Endogenous Charging Coordination

To implement a feedback-loop within an EV population model, one can no longer formulate individual agent decisions on a myopic base but needs to account for

[2] Sioshansi and Short (2009) note that imperfect price forecasts can ensure improved coordination results.

actions taken by other agents. Clearly, endogenous charging coordination is only relevant in the context of smart charging behavior. Therefore, this section only addresses optimal and heuristic smart charging.

Flath et al. (2013) extend the prior work on EV charging coordination by explicitly accounting for both the temporal and the spatial dimension. Their area-pricing approach facilitates price-based EV charging coordination while at the same time accounting for local distribution constraints. This mechanism is used in the following to illustrate both the potentials and the challenges for modeling coordination mechanisms with feedback loop. A key concern is the temporal structure of agent decision-making. For optimal smart charging, it is necessary to adopt a sequential agent decision model while for heuristic smart charging a quasi-parallel one can be applied.

Area Pricing Mechanism

Under the area pricing mechanism EV charging costs are split into two components, the exogenous wholesale electricity price and a locational price dependent on the transformer load level at a given area (Flath et al., 2013). The latter is calculated using an appropriate convex function increasing in the load level.[3] In the following I rely on the specification provided by Flath et al.: Denoting substation maximum load at location x by Φ_x^{lim} and utilization by $z = \frac{\Phi_{t,x}}{\Phi_x^{lim}}$, one obtains

$$p_{t,x}^{loc} = \begin{cases} \frac{e^{3z}-1}{e^3-1} p_{lim}^{loc} & \text{if } z < 1 \\ \tilde{\mathbf{p}} & \text{if } z \geq 1. \end{cases} \tag{7.1}$$

Note that I choose the median of the wholesale price vector $\tilde{\mathbf{p}}$ as the maximum locational price obtained at the maximum utilization level. Furthermore, an arbitrary value of 3 is selected for the functional form of locational pricing function. For a sensitivity analysis with respect to this parameter the reader is referred to the original paper Flath et al. (2013).

To apply the area pricing mechanism the locational price needs to be continuously updated whenever a load change occurs. This updating requires a proper integration into the bottom-up population model depicted in Figure 7.1. The following sections illustrate how this is achieved for the cases of optimal and heuristic smart charging.

Sequential Decision Agent Decision Model

Optimal charging policies need to be formulated over the complete time horizon, whereas heuristic charging decisions are formulated on a single time slot base. Therefore, when determining the charging behavior of an individual vehicle implementing optimal smart charging one needs to specify a stable optimization environment. In the case of cost optimization, this means providing a charging cost vector

[3] Without loss of generality, I abstract from other load types and exclusively focus on EV charging loads.

spanning the entire time horizon. The coordination mechanism providing this price vector can thus only be updated by internalizing an EV's complete charging policy. I refer to this as "vehicle-based aggregation" as complete charging policies of individual vehicles are aggregated. Figure 7.6 illustrates the corresponding work flow with two loops — an outer one for vehicle indices, an inner one for time steps. The mechanism update is called from the outer loop.

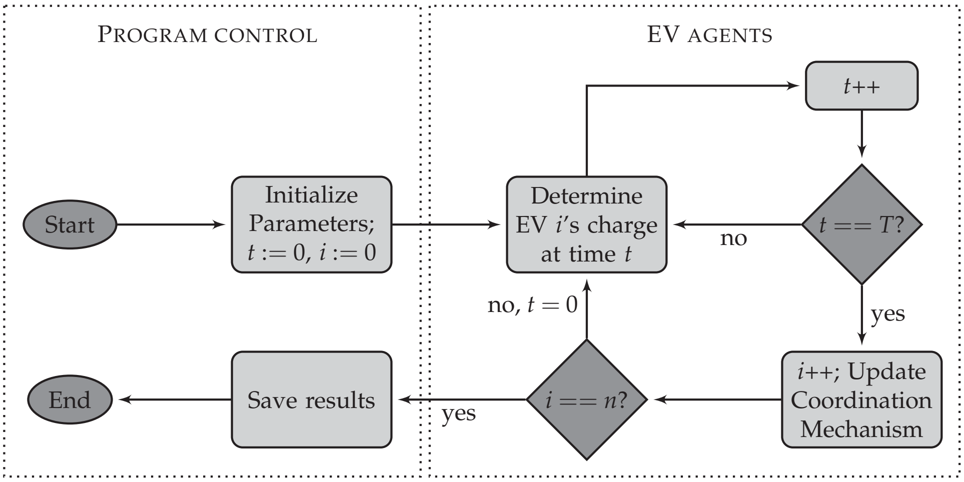


Figure 7.6: Model work flow for vehicle-based aggregation

This mechanism update restriction limits EV agent interactions to be unidirectional, i.e. an earlier vehicle influences the decision problem of a latter vehicle but not vice versa. Clearly, this is a crude approximation as charging decisions will typically be made simultaneously. By sequentially running individual vehicles one can still approximate emergent behavior. However, one needs to bear in mind that inaccuracies may arise from this posited sequential decision-making structure. This especially limits the capability of assessing welfare-effects of coordination approaches.

Quasi-Parallel Decision Agent Decision Model

Given the limitations of vehicle-based aggregation, it would be preferred to update the coordination mechanism more frequently. Given its simple structure with independent charging decisions, the heuristic smart charging policy can be invoked on a per time step basis to obtain aggregate population charging decisions. This allows to exchange the loops compared to vehicle-based aggregation scheme and iterate over time and in each time slot over the EV population aggregating individual decisions (and updating the coordination mechanism) after each time slot.

While time-based aggregation per se allows updating the mechanism more frequently, individual charging decisions per time slot are still only influenced by decision made by preceding EV agents. However, one can further leverage the independent charging decision property and achieve more granular charging decisions by breaking every time slot t into m sub-intervals and apply time-based aggregation after each increment. This yields independent charge fractions

$$\psi^i_{t,j} \in \left[0, \frac{\bar{\phi}}{m}\right],$$

such that

$$\phi^i_t = \sum_{j=0}^{m} \psi^i_{t,j}.$$

The corresponding heuristic charging amounts are then obtained using Equation (6.17) with charging capacity adapted to $\frac{\bar{\phi}}{m}$. Figure 7.7 shows the program flow for time-based aggregation with charging granularity. Note that for $m = 1$ the j-decision in the lower right will always follow the "yes" path reducing the program to two loops. These loops are interchanged compared with Figure 7.6.

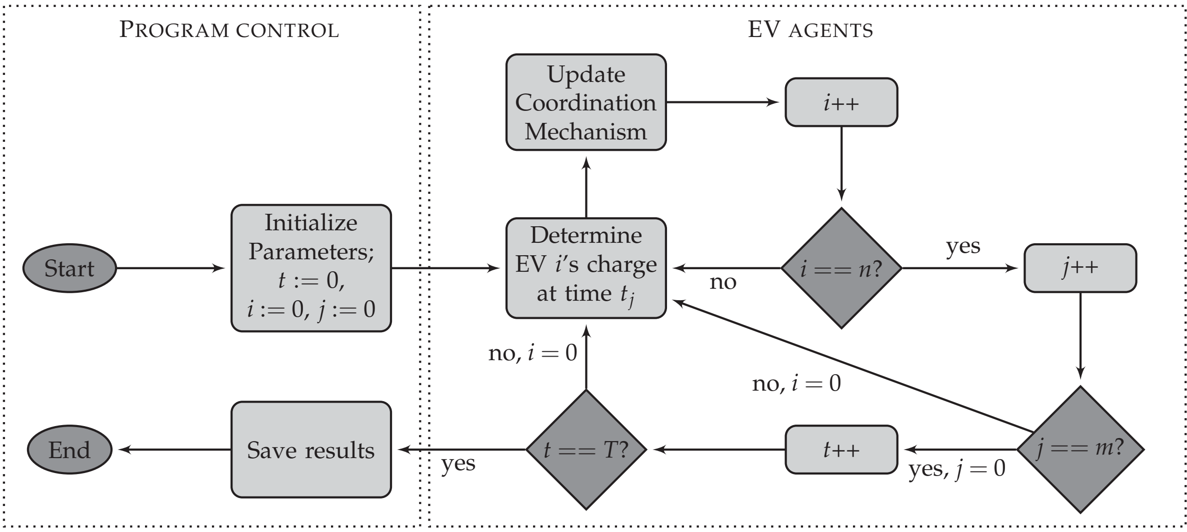


Figure 7.7: Model work flow for time-based aggregation with charging granularity

Within this aggregation scheme, any single fractional charge decision is still formulated in a myopic manner concerning the other agents. However, on a time-step base, charging decisions are taken in a quasi-parallel fashion. To illustrate the difference between the results from simultaneous and sequential decision-making in the presence of a coordination mechanism, one can consider the following: Under area pricing for EV charging, increased charging activity at a given point in time at a certain location will result in an increased grid surcharge. This induces inter-agent interactions as agents may price one another out of the system. The aggregation approach used when creating the population model is crucial to appropriately reflect this effect.

In a non-granular model ($m = 1$), Equation (6.17) will yield either no charging or charging at full power. However, by introducing charging granularity, the charging decisions do no longer exhibit this bang-bang structure but feature intermediate charge levels (which are multiples of $\bar{\phi}/m$) arising from agent interactions through the area pricing mechanism. This is illustrated in Figure 7.8: For $m = 1$ one can see bang-bang charging behavior with agents coming first securing themselves low prices and charging at full power (if their battery level permits) and subsequently driving up the area price, thus pushing out later EVs. With charging granularity exceeding unity, each decision governs only a fractional charge allocation and one obtains a more equitable distribution of the available capacity as illustrated by smoother distribution in the histogram.[4]

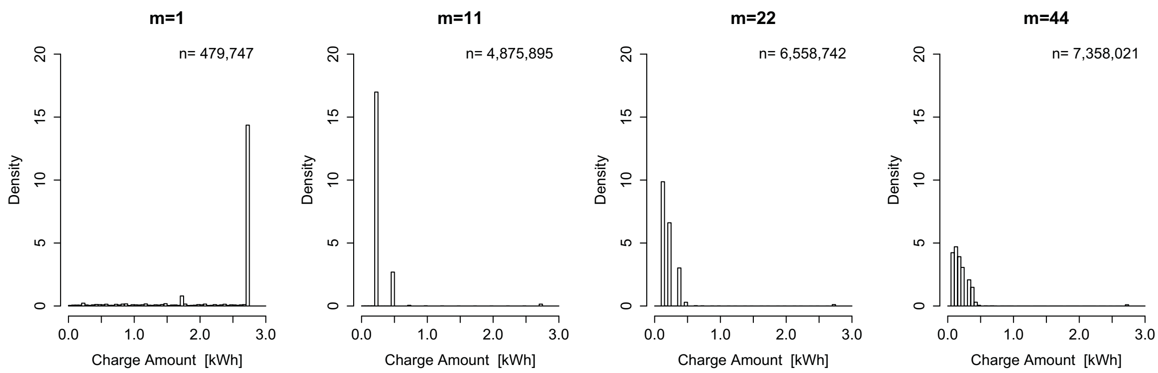


Figure 7.8: Charging behavior for different charging granularity levels (Zero charging amounts are not displayed)

Area Pricing Results

Having established proper models for implementing the area pricing mechanism for EV populations (using optimal or heuristic smart charging), I want to evaluate the aggregate load behavior using the locational price as given by Equation 7.1. Figures 7.10 and 7.9 show the resulting aggregate loads at the *Home* and *Work* location as well as the locational prices at the *Home* location using heuristic and optimal smart charging.[5]

As charging is triggered by low electricity prices, the area price component increases greatly in time slots with low EPEX spot prices. Notably, the locational price never reaches the limit price p_{lim}^{loc}. This also indicates that the local load limit Φ^{lim} is never violated. Compared to Figures 7.4 and 7.5, one can see distinctly more charging activity at the *Work* location. Therefore, area pricing induces both temporal and spatial shifts in individual charging decisions and reduces load peaks significantly. At the same time, load-generation matching is maintained with charging occurring primarily in time slots with low wholesale electricity prices. Comparing heuristic and optimal smart charging, one can see that the heuristic is more often forced into emergency ALAP charging than without area pricing (the jagged load peaks at both *Home* and *Work* prior to typical commuter departures). This is not too surprising, as the area pricing increases the overall price level while the price threshold is still formulated only with respect to the wholesale prices. Therefore, area pricing reduces the amount of price-based charging and the agents are often exhibiting low battery levels with respect to the ALAP threshold or the minimum SOC. Therefore, the overall price increase due to area pricing needs to be properly accounted for by adjusting the heuristic's parameters. Figures F.1, F.2 and F.3 in the Appendix show the

[4]Note that I select the m-values from multiples of 11 to better match the maximum charging power of 11kW.

[5]The depicted locational prices represent the level reached after the final EV's charging decision.

results for alternative parameter choices leading to more coordinated load behavior in the case of heuristic smart charging with area pricing.

The detailed analysis with different charging speeds in Table 7.4 illustrates that total average charging costs are distinctly lower than the benchmark naïve charging without area pricing (Table 7.1). Overall, area pricing succeeds in keeping the local loads within the designated limits at all locations while still enabling EV owners to take advantage of low-cost generation. These results show that area pricing schemes can prevent aggregate load spikes exceeding stability limits by incentivizing load shifting to times *and* locations with lower level of local demand.

Table 7.4: Impact of maximum charging speed $\bar{\phi}$ and charging strategies on average costs, average SOC levels and load spikes. $SOC_{\text{init}} = 100\%$, $SOC_{\text{terminal}} = 90\%$. Profiles infeasible at low charging power levels have been removed in the corresponding columns.

			$\bar{\phi}$ [kW]			
			3.7	7.4	11	22
OPT	Avg. wholesale costs	$[\frac{€}{kWh}]$	0.141	0.141	0.141	0.140
	Avg. locational costs	$[\frac{€}{kWh}]$	0.022	0.022	0.022	0.022
	Avg. SOC	[pct.]	71.6%	72.5%	72.4%	72.4%
	Overloads	[pct.]	0.0%	0.0%	0.0%	0.0%
	Max. Load	[kW]	1,650	1,654	1,652	1,661
HEUR	Avg. wholesale costs	$[\frac{€}{kWh}]$	0.174	0.175	0.175	0.175
	Avg. locational costs	$[\frac{€}{kWh}]$	0.017	0.018	0.018	0.018
$\underline{SOC} = 0.3$	Avg. SOC	[pct.]	75.6%	76.0%	76.2%	76.5%
$\underline{p} = 0.3$	Overloads	[pct.]	0.0%	0.0%	0.0%	0.0%
	Max. Load	[kW]	1,598	1,643	1,642	1,643

Individual Effect of Area Pricing Mechanism Besides its coordination efficiency, the individual effects of the area pricing mechanism are also of interest. Figure 7.11 depicts the average locational prices (as determined via Equation 7.1), wholesale prices (for 10 weeks from 2010) and total costs per kWh paid by the individual EV agents under heuristic charging with three different levels of charging granularity ($m = 1, m = 11, m = 44$). One can clearly see that total costs per kWh are primarily determined by the average wholesale price with the locational price playing a smaller role. Moreover, locational costs are smaller for agents that pay higher total costs as they need to charge during times of high wholesale prices (due to low charging flexibility) when locational prices are typically low. The total cost distributions are very similar to the ones identified in Sections 6.4 and 6.5. Thus, area pricing does not fundamentally alter agent payments.

However, the individual impact of different charging granularity levels is very pronounced. For $m = 1$, one obtains very heterogeneous locational and wholesale price averages. This is because "early" agents can secure themselves both low wholesale prices and low locational prices (because load levels are low) while later agents have to either accept high locational prices (load levels have grown) or need to move to higher wholesale prices. For high granularity values (i.e. quasi-parallel

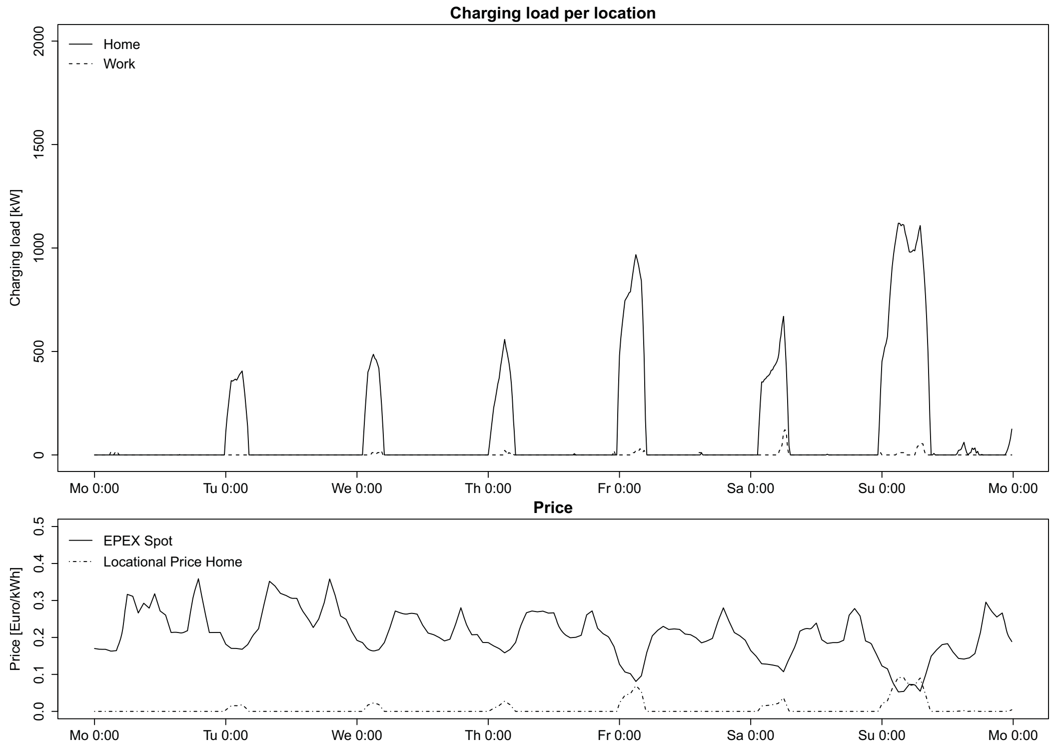


Figure 7.9: Aggregate load under optimal smart charging with area pricing ($\bar{\phi} = 11kW$, $SOC_0 = 100\%$, $SOC_T = 90\%$)

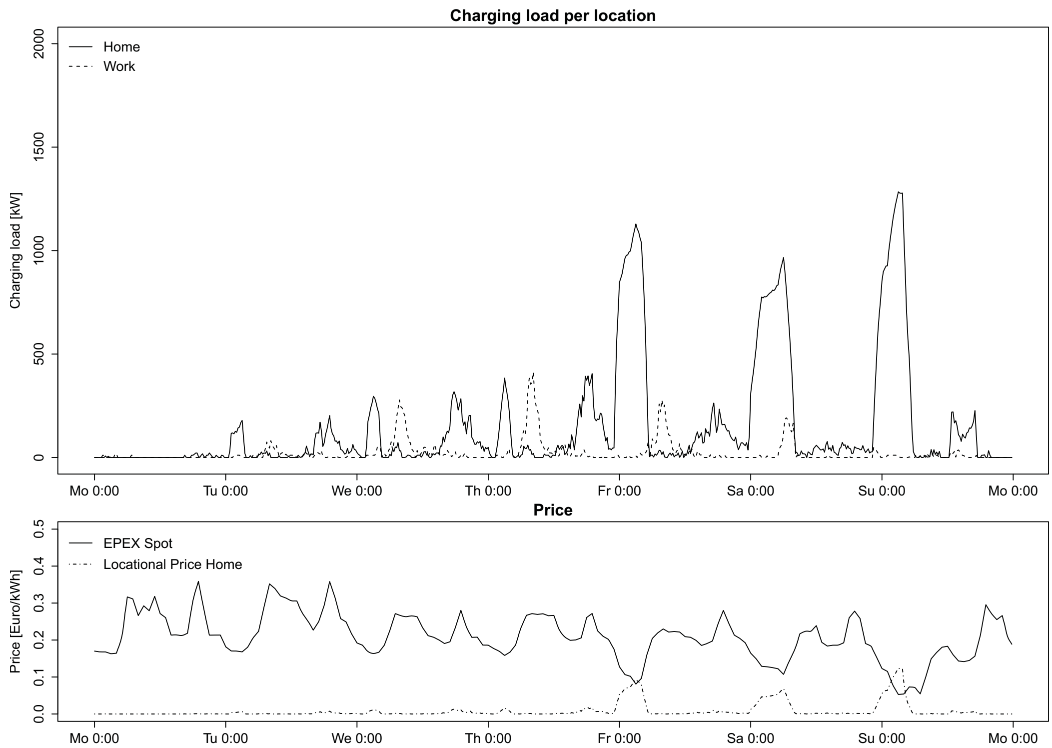


Figure 7.10: Aggregate load under heuristic smart charging with area pricing ($\bar{\phi} = 11kW$, $SOC_0 = 100\%$, $SOC_T = 90\%$, $\underline{p} = 0.3$)

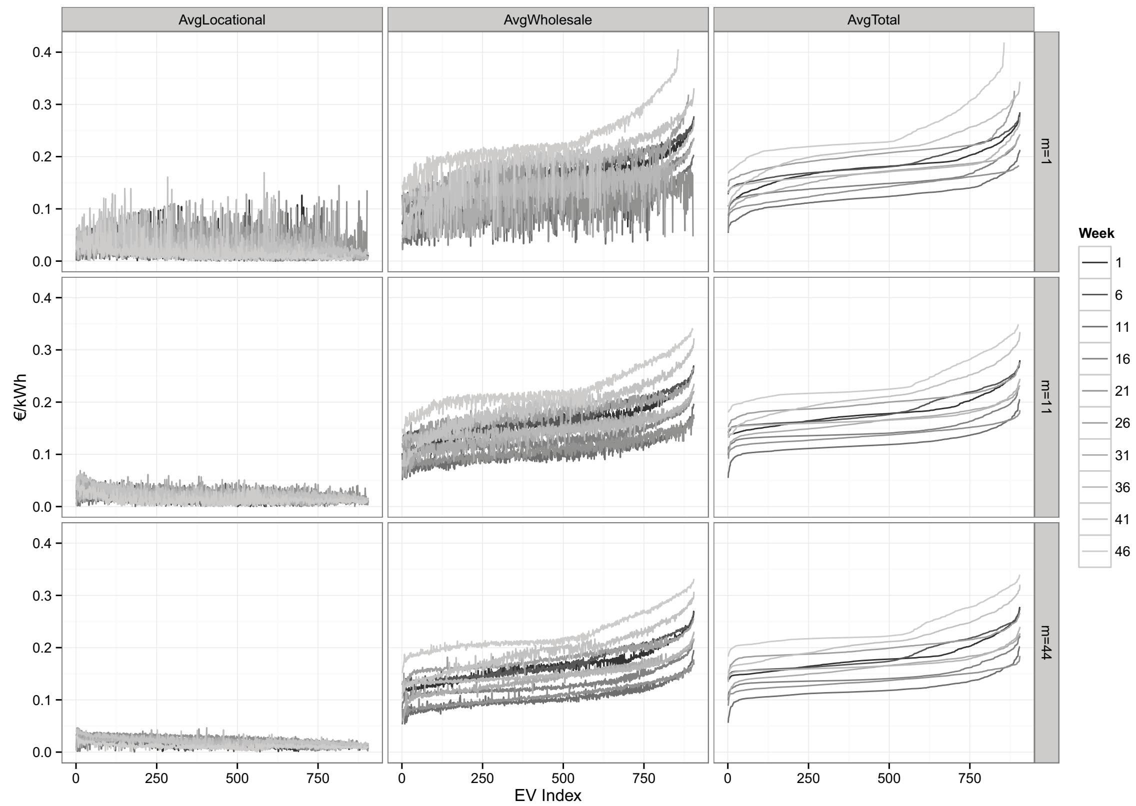


Figure 7.11: Average Charging Costs per EV for 10 Example Weeks

decision-making), the area pricing mechanism induces only minimal distortions of the agents' optimal decisions (average wholesale costs are very similar to average total costs). This is an important insight as it ensures effective load coordination by mitigating overloads. This observation is confirmed by the histograms shown in Figure 7.12. At low granularity levels one can find a distinct mass at very low average wholesale prices. This mass progressively vanishes for increasing granularity while the mass at high wholesale levels moves to the left. The population-wide range of realized charging costs thus becomes less spread out. This reflects a more equitable distribution as there are fewer occurrences of very low and very high charging costs and more occurrences of intermediate cost levels.

7.1.4 Summary and Future Research

This section showed that uncoordinated charging of EV populations tends to create load peaks during system peak times. On the other hand, charging coordination based on exogenous wholesale prices induces significant load spikes during low-price times (avalanche effects). This motivates the introduction of endogenous coordination mechanisms which include a feedback loop. The area pricing approach (Flath et al., 2013) achieves charging coordination with respect to both load-generation matching on the system-wide level and preventing local transformer overloads. The pricing mechanism lends itself to adjustments as well: Currently, the price for charging in an area reflects utilization of the grid capacity. It may be ben-

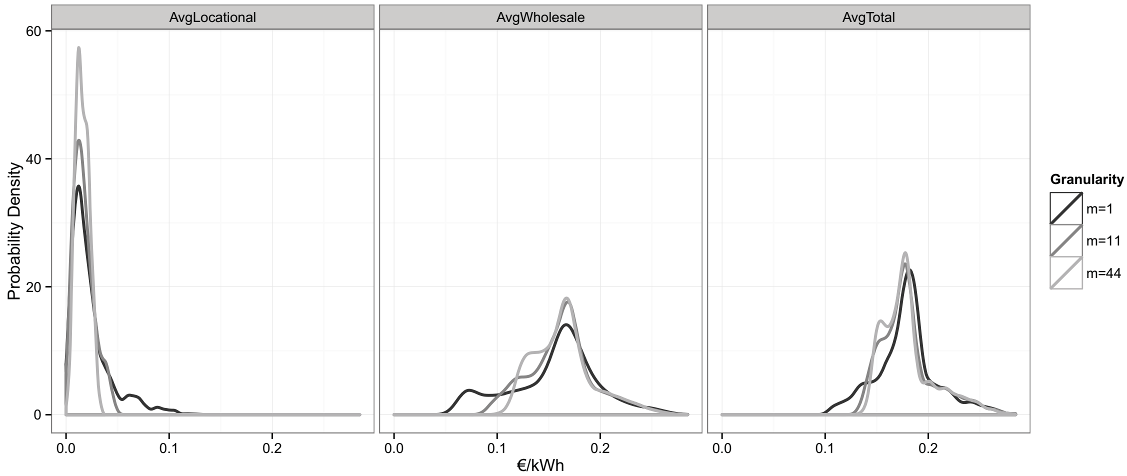


Figure 7.12: Distribution of Payments

eficial to segment customers according to their charging needs and offer segment-specific rates.

7.2 Top-down Population Model and Coordination

As outlined in Chapter 3, for certain applications the usage of micro-founded bottom-up population models may not be warranted given limited data availability or computational constraints. Still, questions of aggregate/ emergent effects of a given EV population on grid loads need to be evaluated in these settings. This motivates the development of adequate top-down approaches.

As noted before, the EV charging capacity of a transformer substation may constitute a bottleneck when charging occurs in a highly clustered manner. When aiming to protect system stability by avoiding transformer overloads, one can optimize the utilization of the capacity trying to maximize the number of customers served while respecting capacity limits. However, coordination approaches that just maximize penetration of EVs are too shortsighted since they ignore the presence of different customer valuations for charging capacity. By adapting capacity control mechanisms from Revenue Management (RM), more efficient allocation schemes can be identified. First, charging coordination is formalized as a minimal revenue management problem. Then an appropriate advance sale mechanism is characterized. By accounting for heterogeneous customer segments, this approach can achieve a socially efficient allocation of available charging capacity. Using a local neighborhood scenario, I evaluate the potentials of such an approach.

7.2.1 Revenue Management

The central operational challenge when managing limited capacity circles around the trade-off between idle capacity and availability. Firms are hesitant to overprovision costly physical capacity and thus adapt management strategies to optimally utilize available resources. Firms will typically optimize capacity usage with the objective of enhancing revenue or profits. Hence, the RM is the common term for management strategies aiming at better capacity utilization.

RM provides firms with decision tools and processes to better leverage demand potentials. It requires an integrated approach with respect to both organizational units (e.g., marketing, operations) and decision scope (strategic and tactical). On the strategic level, firms set capacity levels and long-term demand management while on the tactical level they make pricing and quantity decisions (Talluri and van Ryzin, 2004). RM has its origin in the airline industry (Rothstein, 1971). Today, it is widely applied in other capacity-constrained industries, e.g., hospitality services and car rental (Talluri and van Ryzin, 2004). Nair and Bapna (2001) as well as Boyd and Bilegan (2003) describe application scenarios in the internet and e-commerce domain where data availability and service customization offer great potentials for RM.

Revenue management approaches can be categorized into price- and quantity-based control mechanisms (Talluri and van Ryzin, 2004). The former include decisions on how to set prices and how to adjust them dynamically over time. Retail promotions and Business-to-Business (B2B) procurement auctions are typical examples for these mechanisms. Quantity-based demand-management decisions comprise availability control of products and services as well as versioning. Typical approaches are protection limits or bid prices. For capital-intensive resources Wu et al. (2002) propose an options-based approach. An increasing number of utilities are introducing revenue management in the form of dynamic electricity pricing for industrial and residential customers. However, capacity control approaches are typically not applied in the electricity sector: while variable pricing is mainly a metering topic, capacity management requires dynamic control of customer loads. This is only possible in a fully established smart grid.

In general, revenue and capacity management is most effective for situations where the good cannot be stored (e.g., services), capacity is fixed and customers can be segmented. According to Weatherford and Bodily (1992) in these situations, the challenge is to find "the optimal trade-off between average price paid and capacity utilization". They propose the term "perishable asset revenue management" to describe approaches addressing this challenge. In the simplest PARM case, a firm has to control the capacity of a single resource, e.g., tickets for one flight. They also provide an exhaustive taxonomy for structuring PARM problems.

7.2.2 Charging Coordination as a PARM Model

Like services, EV charging capacity cannot be saved. Moreover, it is fixed in the short term since power system and grid upgrades require substantial investments. Therefore, the charging coordination problem can be interpreted as a PARM problem. The extensive revenue management literature on these problems provides guidance and well-established control strategies (e.g., protection levels or bid-prices) which may lend themselves to application to EV charging coordination. These observations suggest to apply PARM-like modeling to EV charging coordination. The goal is to properly formalize the relevant resource and demand terms to be able to apply well-established mechanisms from the revenue management literature. This way, residential EV charging coordination can be transformed into a RM problem. I focus on managing the EV charging capacity on the distribution grid level. More specifically, the capacity of a suburban neighborhood transformer substation. This is a key challenge for future scenarios where a significant number of commuters own EVs and want to charge their cars at home. The following sections describe how to model and formalize the charging capacity and the demand characteristics of the customer population.

Charging Capacity Model

In the model, the transformer's power capacity is considered as the single, fixed bottleneck in the distribution grid. Furthermore, a single charging period is considered and customers are required to charge at a constant power over the charging period's length T. Let P denote the aggregate available transformer power rating. The local utility will want to reserve an amount δ of the transformer capacity for non-charging activities in the neighborhood. The transformer capacity available for charging is then $P_c = (1-\delta)P$. During any given charging period a charge energy amount of $C = P_c T$ is available for EVs as depicted in Figure 7.13. For such a control strategy to work electricity providers need to handle EV charging through individual rate agreements separated from standard household loads. This is in line with observations in the real world where several energy providers offer EV-specific tariffs.[6]

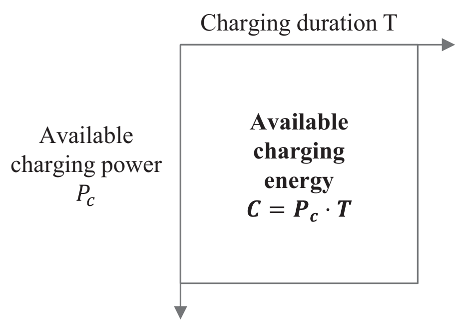
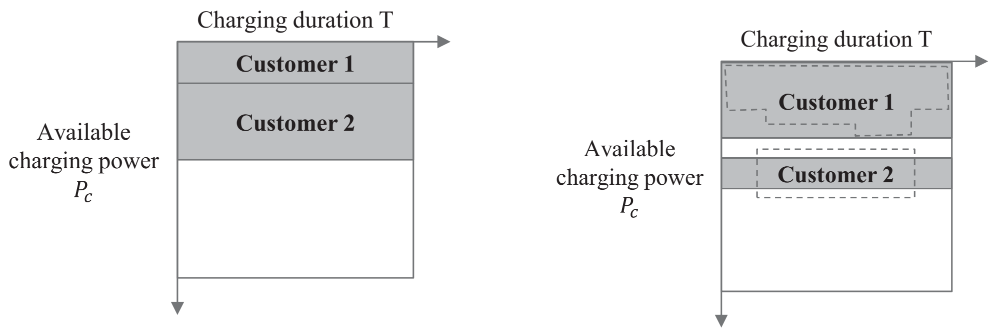


Figure 7.13: Stylized capacity model

When customer j demands a charge amount d_j, she will "occupy" a constant power level of d_j/T over the course of the charging period. This is depicted in Figure 7.14a. Although customers are requesting a charge energy amount, they effectively need to choose a charging power level. Assuming constant charge power, customer requests will always be "rectangular" in the graphical representation. For sake of brevity and without loss of generality, the analysis is restricted to the charging demand terms d and the aggregate capacity C. As customers' charging requests may be of arbitrary size capacity C is continuous. This is a slight variation of typically discrete capacity units (e.g., seats or rooms) in classic RM problems.

[6]An example for such a rate offering can be found at Pacific Gas & Electric in California: `www.pge.com/myhome/environment/whatyoucando/electricdrivevehicles/rateoptions/`.

Using the above-mentioned restrictions on charge requests allows us to reduce the problem to a single-dimensional allocation problem of the total charging capacity C. This makes the problem computationally more tractable than with varying charge power or total charge durations shorter than T. Given our scenario of overnight charging at home, the restriction to rectangular charging programs still provides a meaningful research setting. Furthermore, more general charging programs can be approximated by equivalent rectangular ones with identical area (optimistic approximation) or by using the convex hull of the charging period and the charge power requests (pessimistic approximation). These approximations are illustrated in Figure 7.14b).



(a) Charging at continuous level over complete charging period

(b) Approximation of general charge programs

Figure 7.14: Representation of continuous and general charging programs

Allowing customers to vary both charge power and timing gives rise to a bin-packing problem where the optimal scheduling of charge jobs needs to be evaluated — i.e. the optimal fitting of charge jobs into the available charging capacity. Such richer settings may be necessary for the analysis of other scenarios and provide interesting opportunities for future research. The literature on parallel machine scheduling problems (Cheng and Sin, 1990) and revenue management for flights with multiple legs (You, 1999) provide relevant analogies for tackling more general model specifications. In the following, only the continuous charging case is considered.

Customer Demand

Customer heterogeneity is a central element for characterizing the demand for services. It is also the cornerstone of revenue management approaches. In this model, there are two distinct demand types which are represented as independent "trip populations". These populations encapsulate different trip types, commuting (*regular*) and other driving purposes (*spot*). Each trip type has randomly distributed charging requests. These trip populations originate from a common set of EV customers as described in Chapter 6 — i.e. EVs are used for both regular and spot trips. Demand from these two segments arises strictly sequentially, d_r before d_s — the subscripts representing regular and spot demand. Yet, the charging activity itself occurs over the same charging period, as specified by the capacity scenario. Both regular and short-term demand arise very close to the charging time (e.g., on the same day). Therefore, last minute changes or cancellations are not considered.

Demand Model

A trip population i consists of n_i trips which each yield a demand of a stochastic charge amount $d_{i,j} \sim F_i$, where F_i is a population-specific probability distribution. The $d_{i,j}$ are treated as independent random variables arriving in random order. A customer j from either segment i faced with a capacity shortage ($d_{i,j} < C_{available}$) is assumed to accept a partial charge $d_{i,j}^{\text{partial}} = \min\{d_{i,j}, C_{available}\}$.[7] When dealing with capacity limitations, this assumption allows us to aggregate the demand of the trip populations into a single demand term each. The total segment demands are then given by

$$D_i = \sum_{j=1}^{n_i} d_{i,j} \quad i \in \{r,s\}. \tag{7.2}$$

Demand Distribution

As discussed in Chapter 6, daily travel length of limited-range vehicles can be represented using a Gamma distribution (Greene, 1985) as it allows a reasonable representation of individual empirical driving profiles. Given an approximate one-to-one correspondence between driving distance and energy consumption γ, daily battery discharge amounts obtain to be Gamma-distributed as well. For ease of exposition, I restrict my attention to an Erlang distribution case instead of the more general Gamma distribution. The Erlang distribution obtains as a special case of the Gamma distribution with the set of shape parameters restricted to strictly positive integers — the shape value of 2.064 as given in Equation (6.1) being fairly close to being integral. To properly cast from driving distance to consumption amounts, multiplying the scale factor by the consumption factor $\gamma = 0.129 kWh/km$. Hence, charging demand d_j is Erlang distributed with $Erl(\alpha_i, \gamma\theta_i)$. The shape parameter α_i and scale parameter $\gamma\theta_i$ for regular and spot customers are chosen to appropriately reflect the differences in driving patterns.

Leveraging the analysis from Section 6.1, *regular* trip demand is constituted by commuter trips to the workplace. Given the values from Equation 6.1, an Erlang distribution with $\alpha_r = 2$ and $\theta_r = 3.038\gamma$ obtains. In the scenario at hand, I assume charging at home only. Therefore, the commute distance needs to reflect driving to and from the workplace which implies doubling $\theta_r\gamma$ to 6.076γ. Thus commute round trips have a mean charging requirement of $\mu_r = \alpha_r\theta_r\gamma = 12.152\gamma$ [kWh] with a standard deviation of $\sigma_r = \sqrt{\alpha_r\gamma^2\theta_r^2} = 8.593\gamma$ [kWh].

Assuming that *spot* demand is made up of all unique-length non-commute trips one can characterize two distinct types of trips. An analysis analogue to Section 6.1 indicates that the non-commute round trips in the German mobility panel are Erlang-distributed with $\alpha_s = 1$ and $\theta_s = 37.400\gamma$.[8] Note that for $\alpha_s = 1$ the Erlang distribution collapses to an exponential distribution with $\lambda = \frac{1}{\gamma\theta_s}$. This yields $\mu_s = \sigma_s = 37.400\gamma$ [kWh].

[7] For sake of brevity the superscript "partial" is dropped in the remainder.

[8] Again, the Gamma-fit shape value is close to being integral with an exact value of 0.984.

The corresponding Probability Density Function (PDF) and Cumulative Distribution Function (CDF) of the obtained demand functions are depicted in Figures 7.15 and 7.16. Unlike Figure 6.1 which reports travel demand in trip lengths, these distributions express this quantity in terms of required charging energy. Given a greater underlying trip heterogeneity, the spot demand distribution is clearly less concentrated.

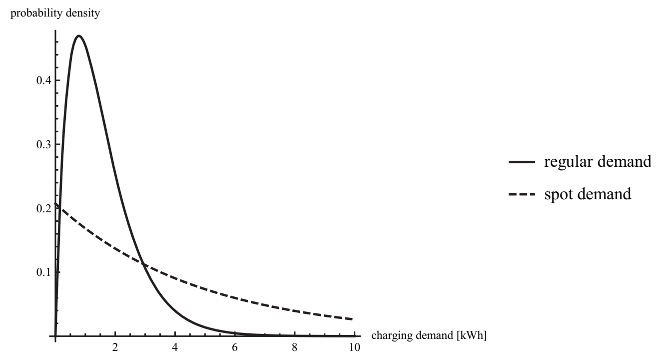


Figure 7.15: Probability density functions of spot and regular demand

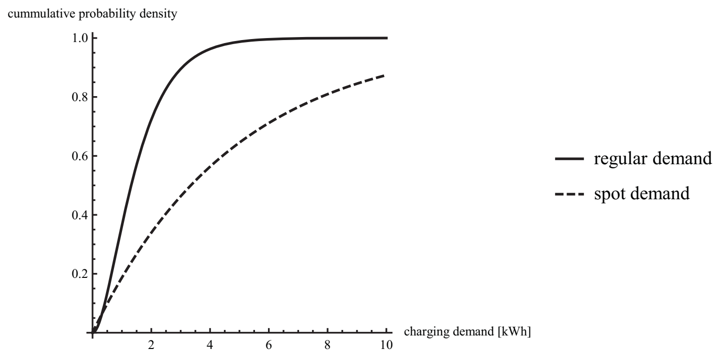


Figure 7.16: Cumulative probability density functions of spot and regular demand

Customer Welfare

Given its more spontaneous occurrence the willingness to pay per capacity unit of short-term charging, v_s, is assumed to be higher than the valuation v_r for charging capacity serving commodity-like regular demand for commuting trips. In the latter case, outside options such as public transport or ride-sharing may be more readily available or can be organized ahead of time. Therefore, $v_r < v_s$. Such higher price-sensitivity of early demand is a standard assumption in the revenue management and services marketing literature (Weatherford and Bodily, 1992; Xie and Shugan, 2001).

I will abstract from prices and revenue and rather optimize with respect to total welfare.[9] This simplification again offers many opportunities for extending the basic model. Denoting capacity allocated to the two trip segments by C_r and C_s (C_s is typically given by the residual capacity $C - \min\{C_r, D_r\}$) this realized total welfare

[9] Weatherford (2004) show that adjustments of the RM objective will still yield meaningful results.

is then given by

$$\Pi = \min\{C_r; D_r\}v_r + \min\{C_s; D_s\}v_s. \tag{7.3}$$

Clearly, the bottleneck of the available charging capacity C only applies if the probability of aggregate demand exceeding capacity is strictly positive. In this case, the value of at least one of the minimum terms in the definition of Π is determined by the allocated capacity value.

7.2.3 Capacity Allocation Approaches

Having established the bottleneck situation in charging capacity allocation, operators should be interested in enacting appropriate management procedures. In the following, I discuss two approaches for handling the capacity shortage — first-come, first served capacity allocation and a two.class reservation scheme.

Simple Allocation of Charging Capacity

As noted before, grid limitations can be addressed either through capacity investments or through load coordination. The simplest form of allocating available EV charging is accepting requests in a first-come, first-served manner until capacity is depleted. However, since the d_r arise before the d_s, the regular demand will have the full capacity available for purchase under this zero-intelligence allocation and coordination rule. See Figure 7.17 for an illustration.

Given the higher willingness to pay of customers for spot trips ($v_s > v_r$), this is not socially efficient if there is excess aggregate demand because spot charging requests may be turned down in case of capacity limitations due to already allocated regular charging requests. A more efficient capacity allocation scheme needs to account for the heterogeneity of the two segments' willingness to pay. At the same time, one needs to account for the stochastic nature of demand which may give rise to capacity idling if less spot trip demand than expected shows up. The next section illustrates how an advance sale mechanism for capacity can achieve this coordination trade-off.

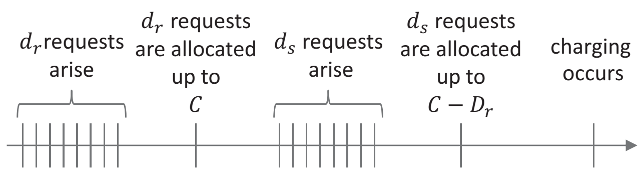


Figure 7.17: First-come, first-served scheme

A Two-Class Reservation Scheme

Charging of electric vehicles occurs frequently — depending on the travel distance daily charging activity is very likely. At the same time, a single charge has very low costs. This stands in contrast to traditional applications of capacity management where transactions are few and more costly. An appropriate control mechanism for residential EV charging should thus feature limited complexity to keep transaction costs low. Bid pricing or capacity options may thus be less appropriate in this setting. As noted by Weatherford and Bodily (1992), the simplest control mechanism for single-resource capacity is the introduction of different discount classes. Limited and discounted advanced sales are a characteristic form of this type of capacity management. Typically, capacity must be limited and marginal costs must be sufficiently small for discounted advance sales to be profitable (Xie and Shugan, 2001). This coincides with the minimal specification of the single resource reservation problem with two discount classes as identified by Littlewood (2005).

As spot demand arises after regular demand, this quantity-based policy requires protecting some capacity for spot trip demand to avoid the opportunity costs of lost sales to high-value spot demand. At the same time, turning down a reservation request yields the risk of not selling the capacity at all and the protection level needs to moderate between these opposed effects. Discounted regular sales are accepted as long as the protection level for spot charging Q_s is not violated. Figure 7.18 illustrates this capacity control mechanism.

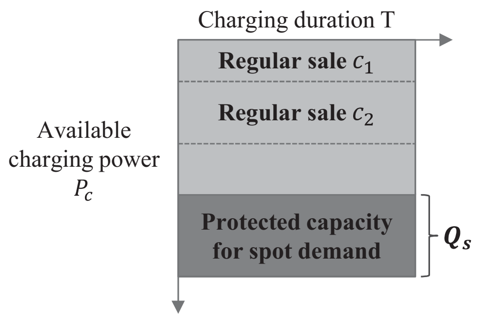


Figure 7.18: Capacity protection mechanism

The sequence of events for the two-class reservation approach is depicted in Figure 7.19. There are always at least Q_s units of capacity available for spot demand. Compared to the non-protection scheme more valuable spot demand can be served, resulting in an allocation of charging capacity that is more efficient. The policy is solely characterized by the protection level which needs to be determined in an optimal manner to ensure high (optimal) coordination efficiency.

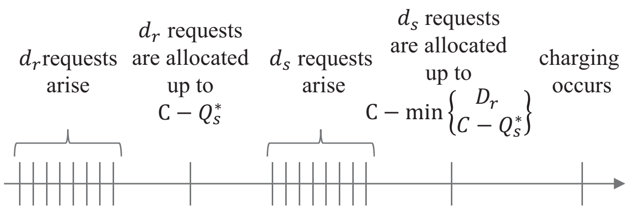


Figure 7.19: Two-class reservation scheme

Optimal Protection Level

In the case of excess demand, protecting capacity curtails allocation to regular trip demand. The welfare gain from an additional protected unit of capacity needs to outweigh this lost welfare. Hence, one can derive the optimal protection level for spot demand Q_s^* with a simple analysis of the marginal welfare gain of both classes. Given a continuously distributed demand, this optimum is characterized by equal values for the expected marginal welfare gain from protecting an additional unit of capacity and the welfare gain of selling the capacity in advance:

$$v_r \equiv v_s \mathbb{P}\left(D_s > Q_s^*\right) \tag{7.4}$$

Denoting the probability density function of demand by $f(x)$,[10] then the CDF of total spot demand for EV charging $\mathcal{F}_s(x)$ is given by

$$\mathcal{F}_s(x) = \int_0^x f(x)dx. \tag{7.5}$$

Using Littlewood's rule (Littlewood, 2005) the optimal protection limit Q_s^* is given by

$$Q_s^* = \mathcal{F}_s^{-1}\left(1 - \frac{v_r}{v_s}\right), \tag{7.6}$$

where $\mathcal{F}_s^{-1}$ is the inverse CDF. Besides the distributional properties of spot demand, the only other relevant economic quantity is the ratio between regular and spot valuation $\frac{v_r}{v_s}$. Clearly, Equation (7.6) is only meaningful for $v_s > v_r$ which comports with our demand specifications. It should be noted, that for a given capacity level the distribution of regular demand actually has no impact on the result and can be considered as a single quantity.

Welfare Expressions

Regular demand D_r arises strictly before spot demand. Without protection, spot trip demand can only be served by the remaining capacity available which is not used by regular demand. The more valuable requests for spot demand can only be served through charging capacity not sold to regular demand. Social welfare is thus given by

$$\min\{C, D_r\} v_r + \min\{\max\{0, C - D_r\}, D_s\} v_s. \tag{7.7}$$

With the introduction of a protection limit Q_s^* regular demand can be turned down and more valuable spot demand can be served to increase social welfare:

$$\min\{C - Q_s^*, D_r\} v_r + \min\{C - \min\{C - Q_s^*, D_r\}, D_s\} v_s \tag{7.8}$$

[10] For the Erlang distribution $f(x;\alpha,\theta) = \frac{x^{\alpha-1}e^{-\frac{x}{\theta}}}{\theta^{\alpha}(\alpha-1)!}$ for $x, \theta \geq 0$.

It can be shown that under risk-neutrality[11], protecting Q_s^* units of charging capacity for spot demand is an optimal policy balancing the gains from being able to meet extra spot demand against the certain loss from turning down regular trip demand.

Optimal Protection Level under Erlang Demand Distributions

As explained in Section 7.2, the Erlang/ Gamma-distribution not only matches the empirical data, it is also distribution-invariant with respect to summation. Aggregate segment demand, D_i with $i \in \{r,s\}$, is the sum of individual charging demand quantities $d_{i,j}$ (Equation 7.2). Each individual demand quantity is drawn from a common Erlang distribution, that is $d_{i,k} \sim Erl(\alpha_i, \theta_i)$. Then, the distribution of total segment is also an Erlang distribution, namely

$$D_i \sim Erl_i = Erl(n_i \alpha_i, \theta_i). \tag{7.9}$$

This is an interesting result as it allows expressing the charging demand of the complete EV population by means of a single expression — a very elegant and compact top-down poulation model.

Following Equation (7.6), one can directly calculate the optimal protection level Q_s^*. Given the heterogeneity in the willingness to pay between regular trip demand and spot trip demand the optimal protection limit Q_s^* obtains as

$$Q_s^* = Erl_s^{-1}\left(1 - \frac{v_r}{v_s}\right), \tag{7.10}$$

where $Erl_s^{-1}(\cdot)$ is the inverse CDF of the spot demand distribution. The inverse of the Erlang distribution involves the inverse Gamma and can thus not be expressed in closed form. However, it is readily evaluated in a numerical manner using appropriate tools as shown in Figure 7.20 for the demand distributions from Figure 7.15 ($n_r = n_s = 1$).

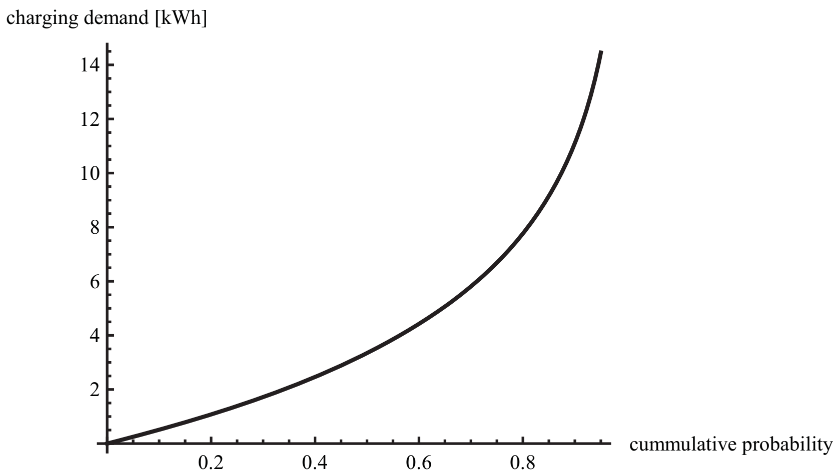


Figure 7.20: Inverse cummulative probability function of spot demand

[11]Risk-neutrality is a standard assumption for firm decision-making. Alternative risk attitudes can be reflected by appropriately adjusting the marginal welfare evaluation in Equation (7.4). See Weatherford (2004) for an in-depth discussion.

7.2.4 Numerical Analysis

Given the unavailability of a closed form inverse CDF for the Erlang distribution, efficiency potentials of capacity protection cannot be determined in a fully analytical format. Therefore, a simple numerical example is used to explore how protecting EV charging capacity can increase total welfare. This example is based on a suburban neighborhood with overnight charging activity.

Scenario and Parameters

A residential neighborhood served by a single transformer substation is considered. It is assumed that this transformer has 220 kW of available power for EV charging overnight, i.e. between 10 pm and 6 am. Furthermore, I assume a total number of 500 EVs in the neighborhood. As in Chapter 6, I assume vehicle consumption to be $0.129 kWh/km$.

Given the commuter scenario, I assume that each EV pursues a daily commute, therefore $n_r = 500$. Our mobility data set indicates that non-commute trips are less frequent with 0.833 trips occurring per commute trip. The analysis uses n_s values between 200 and 400.[12] As noted before, the distribution of regular demand does not economically affect the results. Therefore, I use the population mean to express the regular demand level $D_r = \gamma \cdot n_r \cdot \mu_r = 783.8$ [kWh]. On the other hand, for the spot demand a stochastic term based on the Erlang distribution is applied:

$$D_s \sim Erl_s = Erl(n_s \cdot \alpha_s, \gamma\theta_s) = Erl(n_s, 4.825)$$

v_r is normalized to 1 and v_s is chosen from the range 1 to 5. Thus the ratio v_r/v_s is equal to the inverse of spot valuation, i.e. v_s^{-1}.

Table 7.5 summarizes the most important input parameters for this example of EV charging in a suburban neighborhood.

There is clearly sufficient capacity to serve regular demand, however, in expectation capacity is insufficient to serve both segments. Thus, given the higher willingness-to-pay of spot demand, the charging provider has an incentive to pursue capacity management.[13]

Evaluation

Given the scenario specified above, I am interested in the effects and potentials of introducing an advance-sale capacity management approach. First, the structure of the optimal capacity protection policy is characterized. Subsequently, I look at the welfare effects compared to a naïve first-come-first-served allocation scheme.

[12] Clearly, this is a simplification as the number of spot trips is kept constant and are only varied their length. However, most results should be robust to generalizations of this setting.

[13] As noted before, our analysis focuses on welfare effects. Yet, such an increase in welfare is typically somewhat aligned with provider incentives and the results are indicative for a profit-maximizing operator.

Table 7.5: Summary of input parameters

Parameter	Value
Available transformer capacity P_C	220 kW
Charging duration T	8 hours
Available charging capacity $C = TP_C$	1760 kWh
EV consumption per km γ	0.129 kWh/km
Number of regular trips n_r	500
Daily regular demand $D_r = n_r \mu_r \gamma$	783.8 kWh
Willingness to pay for regular trips v_r	1
Number of spot trips n_s	250–400
Daily mean spot demand $\mathbb{E}[D_s] = n_s \mu_s \gamma$	2011.9 kWh
Spot demand distribution $\mathcal{F}_s$	$Erl(n_s, 4.825)$
Willingness to pay for spot trips v_s	1–5

Optimal Capacity Protection Policy

As prescribed by Equation (7.10), the optimal policy for the charging operator is to offer advance purchases for capacity up to the protection level Q_s^*. For a given spot distribution, i.e. $Erl_s = Erl(n_s, 4.825)$, Q_s^* can be determined for any value of v_s, that is $Q_s^* = Erl_s^{-1}(1 - v_s^{-1})$. Figures 7.22 and 7.21 illustrate the optimal policy for different spot valuations and numbers of spot trips. To better illustrate the effect of increasing spot valuation, two valuation ranges are conisedered — [1;1.5] and [1;5].

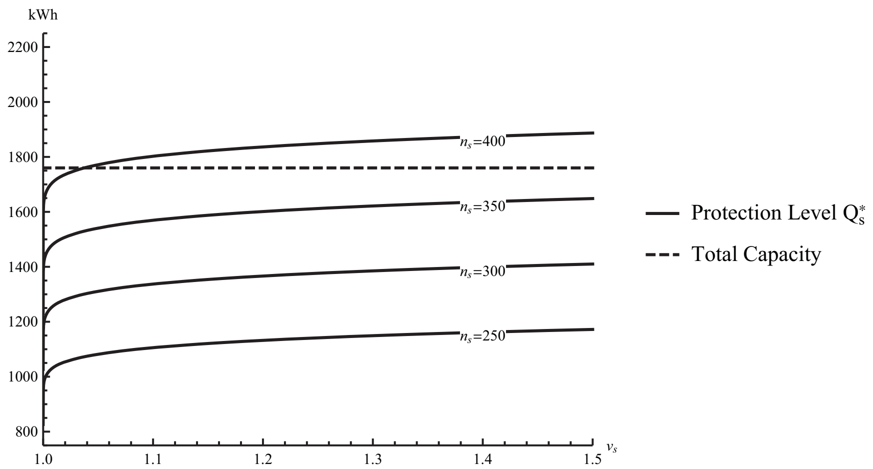


Figure 7.21: Optimal protection level over a different spot valuations, $v_s \in \{1,1.5\}$

The optimal protection level is clearly increasing in both parameters. For the number of spot trips, one can observe an almost linear upward shift which reflects the increasing scarcity of capacity. With respect to valuation v_s, the optimal protection level is increasing in a concave manner. Initially, the valuation ratio impacts the optimal protection level very drastically. For $v_s = 1$ no capacity protection is optimal ($Erl_s^{-1}(0) = 0$), yet a minimal increase in spot is leveraged by the large number

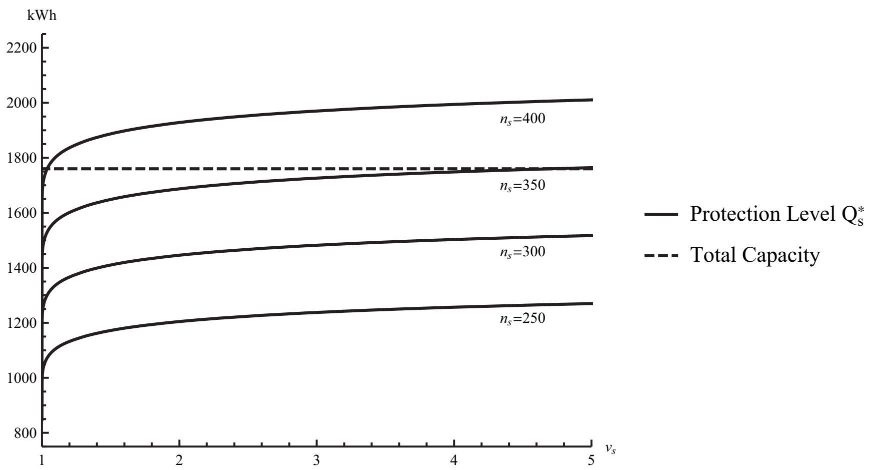


Figure 7.22: Optimal protection level over different spot valuations, $v_s \in \{1,5\}$

of vehicles considered yielding an almost instantaneous[14] jump in Q_s^* to over 1,000 kWh.

Beyond $v_s \approx 1.01$, the evolution of Q_s^* is less extreme. For the $n_s = 400$ case, one finds that advance sales are not efficient in most cases with the optimal protection level exceeding available capacity for v_s values beyond ≈ 1.02. In the other cases, somewhere between 61% and 100% of the available 1760 kWh capacity should be protected.

To further assess the impact of the valuation spread on the optimal policy, it is illustrative to look at the limit $v_s \to \infty$. The corresponding values are given in Table 7.6. Compared to Figure 7.22, the protection continues to increase for even higher valuation spread. When planning a capacity expansion, these limit values can serve as an upper bound for extra capacity required for serving spot demand when pursueing a strict availability objective.

Table 7.6: Limit values of protection level ($v_s \to \infty$)

Number of spot trips	250	300	350	400
Optimal protection level [kWh]	1510.7	1779.0	2045.1	2309.5
Optimal protection level [% of 1760 kWh]	85.8	100	116.2	131.2

Welfare Results

Besides the optimal policy itself, a special interest lies in the aggregate welfare effect of capacity management. This requires evaluating the expected spread between Equations (7.7) and (7.8). Again, this expression cannot be derived in closed form, due to the presence of the Erlang inverse CDF. Therefore, I use the `NExpectation` function provided by Mathematica[15] to obtain the expected values numerically.

[14]Note that since Erl_s has support over $[0,\infty]$, Q_s^* is differentiable for all values spreads. However, the numerical approximation becomes unstable at v_s close to zero.

[15]www.wolfram.com/mathematica

Figure 7.23 shows the development of welfare obtained under capacity-protection (normalized by baseline first-come-first-served welfare) for different values of v_s and n_s. The results show a clear welfare increase for protecting EV charging capacity in comparison to a first-come, first-served charging policy. As for the optimal protection policy (Figure 7.22), the key influence factors for the efficiency of capacity protection are the valuation ratio and the number of spot trips. The effect of the value spread diminishes for increasing v_s. Similarly, the effect of the number of trips n_s is proportional to this effect and homogeneous for each 50 spot trip increment.

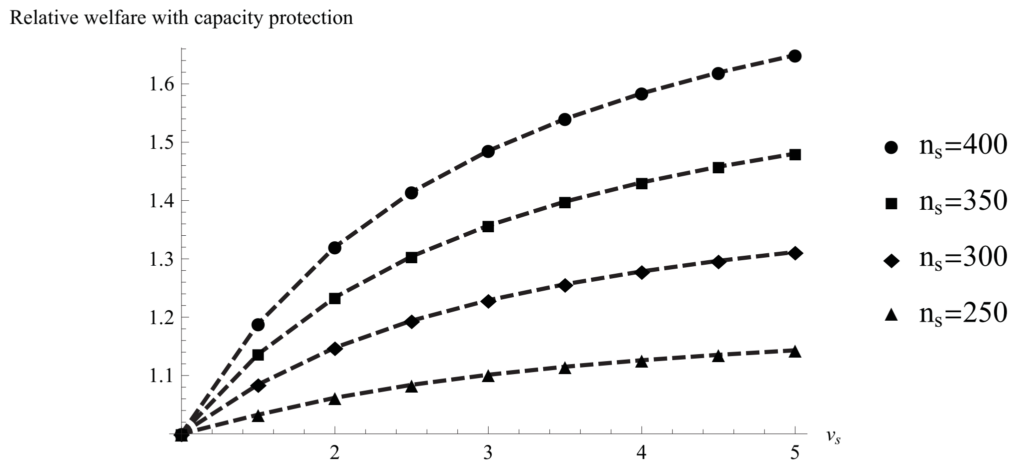


Figure 7.23: Relative welfare level with capacity management (versus first-come-first-served base-case)

Unused Capacity

While the first-come-first-served pattern maximizes capacity utilization (expected utilization across all parametrizations is very close to 100%), the introduction of capacity protection inherently results in unused capacity, i.e. capacity protected for spot trips but unused in the end due to too limited spot demand. Figure 7.24 illustrates this effect for a setting of unlimited capacity. Clearly, the expected unused capacity is increasing in both the valuation spread and the number of spot trips as more capacity is protected upfront (Q_s^* is increasing in v_s and n_s).

It is also increasing in n_s, however, this is only the case as long as Q_s^* is below total capacity C. This becomes evident in Figure 7.25 where C is again set at 1760 kWh. For $n_s = 400$, spot demand will exceed available capacity in almost all cases and protecting capacity will not result in unused capacity. Similarly for $n_s = 350$, Q_s^* equals C for $v_s > 5$ and the unused capacity remains stable at around 85 kWh. Clearly, these are situations where a capacity expansion is well warranted to serve a greater share of total demand.

7.2.5 Summary and Future Research

Increasing EV penetration levels require coordination of charging activity with respect to both aggregate load management and distribution grid capacities. Coor-

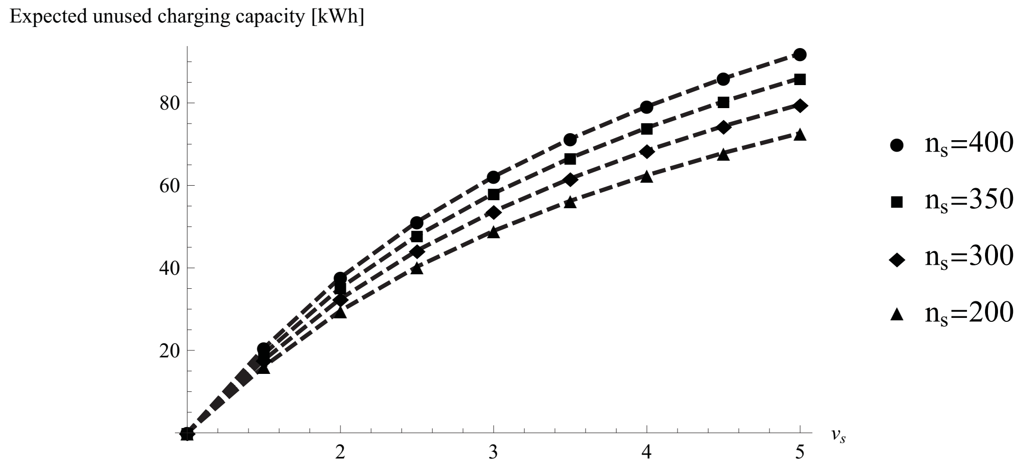


Figure 7.24: Unused capacity arising from capacity protection for $C = \infty$

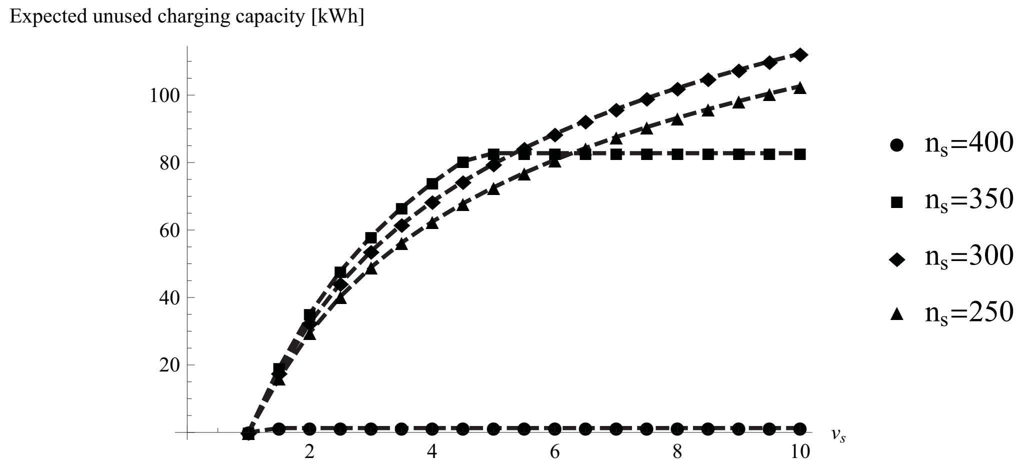


Figure 7.25: Unused capacity arising from capacity protection for $C = 1760$

dination mechanisms for the latter bottleneck are not socially efficient if ignoring customer/ demand heterogeneity. The basic model specification illustrates that coordination of distribution grid capacity for EV charging can be modeled as a PARM problem. A two-class reservation scheme provides an efficient solution to this problem and allows to characterize potential welfare impacts.

Model Summary

The proposed control mechanism is appropriate in situations where transformer capacity is the relevant bottleneck and the commuter scenario with limited trip freedom is applicable. Social welfare increases with the expected utilization of charging capacity. If the expected charging demand greatly exceeds available capacity, an investment in the local distribution grid and transformer capacity is preferable. Table 7.7 provides a classification of the complete model along the taxonomy presented by Weatherford and Bodily (1992).

Element	EV charging
Resource model	single, continuous
Prices	pre-determined
Willingness to pay	buildup
Discount price classes	2
Group reservations	n/a
Diversion	n/a
Displacement	n/a
Show-up of reservations	certain
Bumping procedure	n/a
Decision rule	static

Table 7.7: Classification of basic electric vehicle charging capacity management model following Weatherford and Bodily (1992)

Future Opportunities

This section aims at demonstrating the relevance of RM techniques for addressing the challenges posed by the coordination of EV charging. By providing ample opportunities to expand and improve on, the presented minimal PARM model for EV charging coordination serves as a platform for future work in this direction. The following possible extensions seem especially relevant:

Prices The static welfare approach ignored price and cost effects on demand and supply. Clearly, a provider-centric model would rather have to focus on profit maximization. Furthermore, realizing that power and energy are separate value components of EV charging one can easily envision models where capacity pricing is driven by the price for electrical energy — charging demand may be high when energy prices are low.

Discount Price Classes While a stylized setting with two discount classes is helpful to illustrate the underlying economic mechanics, a richer setting is required to achieve a more realistic model. The RM literature provides a large body of research for handling models with more than two customer segments. Most importantly, the Expected Marginal Seat Revenue (ESMR) decision model proposed by Belobaba (1989) extends Littlewood's model to n customer classes.

Group Reservations Allowing individual customer demand to be dependent on each other creates the possibility of modeling customer groups, especially fleets of EVs. This is especially relevant for car-sharing scenarios where fleet management is an additional challenge (Nair and Miller-Hooks, 2011).

Resource Dropping the single time slot assumption is necessary for modeling applications that are more realistic. As noted before the research on revenue management for multi-leg flights and multi-machine scheduling may guide this extension.

Diversion In a model with multiple sequential charging time slots, the different time slots may constitute substitute products for the customers. This customer diversion both complicates the revenue management problem but also provides the operator with additional degrees of freedom to optimize capacity utilization. Diversion can also occur in a repeated setting with a single time slot. In this case, multiple reservations may be simultaneously opened. This can possibly lead to inter-temporal diversion effects.

Displacement Sequential time slots may also give rise to conflicting customer requests: A customer charging for only one slot can block a customer charging for two slots — such displacement effects are a well-known from multi-leg flights RM.

Show-up of Reservations and Bumping Stochastic show-ups or the possibility to deny service to advance customers for a compensation payment (bumping) may equip providers with additional strategic levers.

Decision Rule In the described model, the static booking limit constitutes an optimal policy. This may not be the case in a more complex setting. However, the limitations on the available control strategies imposed by EV charging characteristics may continue to hold.

Insights from revenue management can have a profound impact on the EV business models of both electrical power companies as well as EV mobility providers like BetterPlace (cf. Section 6.8.2). This notion seems plausible as Kimes and Wirtz (2003) note that capacity management approaches have become very common in diverse industries.

7.3 Discussion

This chapter describes how to model aggregate charging load of EV populations. This insight is used to analyze and discuss different approaches to charging coordination — laissez-faire, exogenous price signals and reservation-based capacity control. Depending on the situation, these coordination approaches may not achieve the goals envisioned in Section 2.2. Appropriate population models are a central input to evaluate the adequacy of alternative coordination approaches and allow to assess the emergent population behavior (Ramchurn et al., 2012) prior to determining and fixing a specific regulatory regime. Such guided design of coordination approaches follows the market engineering paradigm (Weinhardt et al., 2003).

There are ample opportunities to expand the design and analysis of EV charging coordination approaches. An interesting extension of the discussed coordination approaches would be the integration of V2G scenarios where EVs can feed electricity back into the grid (e.g., in times of high prices). This way, the results of Kempton and Tomic (2005) can be investigated in a setting with both uncertainty and grid constraints. Moreover, the current analysis focuses on individual charging behavior. It has often been argued that electrified individual transport may put greater emphasis on vehicle sharing systems (Nair and Miller-Hooks, 2011). Such systems may exhibit greater charging flexibility as requests can be served with the whole fleet which may improve grid integration capabilities. Similarly, the coordination mechanism discussed above are evaluated with respect to static EV behavior characterized by threshold strategies or optimization approaches. Alternative EV charging models such as learning agents (see Section 6.8.2) may warrant alternative coordination approaches (Dauer et al., 2013). Similarly, capacity management models for EV charging coordination offer a rich set of extension possibilities (see above).

Part IV

Finale

Chapter 8

Summary and Future Research

This thesis set out to establish a notion of economic smart grid modeling. Building on previous smart grid research, Part I describes the technological and economic aspects that transform the traditional grid into a smart grid. These insights provide a base for the development of a framework for modeling smart grid customers. Parts II applies this framework to create models representing household and small business customers. Similarly, in Part III electric vehicle charging behavior is modeled assuming different incentive and information settings. Using these models appropriate coordination approaches such as individual TOU rates or area pricing are discussed incorporating the smart grid coordination goals established in 2. This chapter recapitulates and summarizes key findings and concepts from the previous chapters. This summary is guided by both the thesis structure and the research questions put forward in Chapter 1.

8.1 Smart Grid Economics

Smart grids constitute techno-economic systems whose sensor-actuator infrastructure facilitates novel approaches for optimization and coordination of system operations compared to traditional grids. Still, the basic electrical laws of the physical grid govern stability and reliability of the system. Smart grids cannot change the physics of power distribution, but they can help achieve a better utilization of available physical resources through better demand coordination. Therefore, smart grid systems still need to strike a balance between cost efficiency, reliability and sustainability — the classic trilemma of energy economics. However, the enhanced coordination capabilities provide greater degrees of freedom to achieve this balance through active management of different balancing capabilities such as demand response, distributed generation and storage devices. This bouquet of management options will play a crucial role in establishing a power system based on a significant portion of renewable generation. Adopting an economic view, the analysis of smart grid capabilities needs to incorporate physical boundaries and inflexible customer demand as hard constraints which need to be facilitated by means of flexibility potentials and smart dispatching (decision variables). At the same time, decentral decision-making characteristics need to be accounted for — ideally, coordination approaches ensure incentive compatibility on behalf of the distributed agents. Thus the set of relevant coordination bottlenecks (research question 5) in the smart grid is spanned by both physical constraints and agent behavior. Therefore, robust smart grid design requires both technological solutions *and* sound economic design (Chassin and Kiesling, 2008). This thesis focuses on the latter and develops a theory of customer modeling and coordination mechanisms as building blocks for the characterization of smart grid markets (research question 1).

Acknowledging the greater importance of distributed "small" individual customers in the future electricity system, Chapter 3 identifies four levels that should ideally be captured by smart grid customer models. These levels are static customer characteristics, model size and scope, demand response characteristics and model adaptivity over time. The first level requires a basic representation of the fundamental load characteristics of a given customer type. This essentially represents a minimal, static model, e.g., a load curve. The second level considers two distinct approaches of expressing model scope, individual-focused bottom-up versus population-focused top-down models. Depending on the scenario at hand, one approach may be more suited than the other. Similarly, hybrid models can be envisioned. A central goal of smart grids is effective coordination of customers' load flexibility to match stochastic generation patterns from renewable energy sources. Therefore, a proper representation of load response characteristics and capabilities is a very important aspect of a smart grid customer model. Finally, long-term analyses of technology and rate adoption require corresponding model capabilities. Focusing on rate adoption and smart grid investments, tools from marketing research (logit choice) and the theory of investment under uncertainty offer helpful insights to incorporate these model aspects. These four levels jointly address research question 2.

Clearly, the value of such a research framework fundamentally stems from its usage. Both within this thesis and within future research these facets of customer modeling should be incorporated. At the same time, the current framework focuses on the electrical loads. Going forward, a convergence of different energy forms is expected and a more integrated view of load behavior will be required (Lund and Münster, 2003; Block et al., 2008). Extending the notion of energy services (Schweppe et al., 1980; Stroehle et al., 2012) and appropriately integrating these into the smart grid customer modeling framework will be a promising avenue for future research.

8.2 Residential Load Modeling and Coordination

Drawing on the concept of top-down synthetic customer models developed in Part I, the third part of this thesis focuses on the specific case of household and small business load modeling and coordination. Chapter 4 describes the system design and results from a data analysis case study with a regional utility company. By means of standard data mining techniques (KDD, k-Means Clustering, DBI selection procedure) load patterns and similarity information were extracted from a smart meter data set. This way, highly granular customer load profiles can be determined and individual customers can be classified more precisely than using standard load profiles. In addition, initial attempts to extract load flexibility properties from the profiles were discussed. These positive results confirm the corresponding research question 3. Besides providing a base for efficient smart grid customer modeling, the improved classification capabilities also have a direct practical impact as they facilitate both better load forecasting and the design of customized rates. A key goal was the direct integration into available ERP systems to ensure high practical relevance.

The cluster analysis gives rise to subsequent research opportunities. To regionally and temporally validate the robustness of the identified clusters, additional data sets are required. Based on such richer data sets, static household models can also be enhanced using the quantile-based analysis of the load curves. Moving away from average values and acknowledging load variance patterns, additional flexibility information can then be extracted from the raw data. This can be used to implement demand response capabilities in top-down models adopting the techniques described by Esser et al. (2007) and Wang et al. (2010) for micro-founded models. Moreover, the integration of additional data sources such as rate information or demographic household data could be leveraged for better segmentation results. Newsham and Bowker (2010) argue that there is an insufficient understanding to what extent residential customers adapt their electricity consumption considering their socio-economic properties. This is a central question for future demand-centered control paradigms. Therefore, more research needs to focus on assessing load shifting potentials and demand elasticity values. This may require alternative research approaches like surveys or laboratory experiments.

Acknowledging the potential of customized rate designs, Chapter 5 describes and evaluates a MIP framework for optimal design of customized TOU rates. The described approach provides a simple way to express rate structure requirements and to efficiently derive the corresponding optimal rate structure for different objective functions. The analysis shows the advantages of customized rates (versus symmetric rate designs) especially for rates with a small number of rate zones. Furthermore, the evaluation indicates that rate granularity and update frequency play a joint, major role in determining the efficiency of customized TOU rates. Considering both customer acceptance and coordination efficiency, customized rates can be one building block for creating appropriate coordination mechanisms in the smart grid (see research question 6).

The presented analysis currently only considers rate updates specifying a complete rate structure. Alternatively, one could look into partial rate updating that transform the previous rate in a simple manner, e.g., by shifting all price levels up with other rate elements remaining unchanged. Such limited price updates could potentially reduce rate (and communication) complexity and thus assist in increasing customer acceptance. It would be interesting to see, how much welfare is lost through constrained updating and how it interacts with other rate design elements. Similarly, it may be worthwhile to investigate the efficiency impact of other rate design constraints such as minimum zone length, price jump limits or limiting the number of distinct price levels. The effect of uncertainty is especially interesting in the context of rates with longer horizon, spanning, e.g., a whole week instead of a single day. Moreover, the interconnection between demand modeling and rate design is of special interest, especially when determining rates with a profit maximization objective. Consequently, the rate design approach can be applied in conjunction with richer demand models. Finally, behavioral dimensions such as customer acceptance and response to alternative TOU specifications should be analyzed in more detail. Such an integrated approach towards understanding customer decision-making and the evaluation of coordination approaches is a central challenge on the way towards effective smart grid modeling.

8.3 Electric Vehicle Load Modeling and Coordination

The charging activity of a growing number EVs will constitute both a large and flexible load in the future electricity system. This means that EVs may very well play a central role in smart grid coordination constituting a significant load share in distribution grids. Consequently, EV charging activity needs to be carefully analyzed in order to build meaningful and robust smart grid models. Part III addresses this challenge. Key to this material is the modeling of EV charging activity with a special focus on the point raised in Research Question 4 — *What is the impact of price and trip uncertainty on electric vehicle charging behavior?* Chapter 6 develops model building blocks and appropriate charging strategies. By using modified optimal or heuristic decision rules it is possible to leverage the load flexibility inherent to EV charging to ensure low charging costs, even under cost and driving uncertainty. The chapter also provides an indication of the value of different types of information and the cost of requiring certain minimum EV charge levels.

While the charging policies introduced and discussed in this thesis are capable of handling limited information scenarios, they remain static in the sense that they are invariant state-action mappings. Within richer decision settings (multi-modal transportation options, changing price scenarios) such policies may be less effective. Hence, adaptive learning approaches as discussed by Dauer et al. (2013) may become more relevant. In addition to tailoring the charging strategies, an important point is the education and information of EV owners and drivers (Flath et al., 2012). Firstly, to overcome range anxiety the drivers need to be educated on how much range they really need every day. Secondly, based on a specific driving profile the cost drivers for individual mobility can be benchmarked. A bigger battery can for example lead to cost reductions per kWh and therefore to lower cost over the vehicle's lifetime. On the other hand if only short ranges are necessary a large battery may be too large and therefore too expensive. Finally, the future may bring a rise of inter-modal/ hybrid transportation systems. Within such mixed systems drivers will have even more options to choose from and individual decisions will have to be aligned.

Moving away from the individual vehicle perspective, Chapter 7 considers ways to aggregate individual charging decision to a population level. This insight is used to develop and evaluate charging coordination mechanisms based on exogenous and endogenous pricing approaches or charging capacity management. A central result of this chapter is the potential to mitigate conflicts between local and system-wide resource coordination through endogenous pricing which internalizes agent actions through appropriate feedback loops. Similarly, the chapter shows how a simple charging capacity allocation scenario can be framed as a PARM problem.

This provides a base to leverage the large body of revenue management literature to develop improved EV charging coordination approaches.

To conclude, there are ample opportunities to expand the design and analysis of EV charging coordination approaches. An interesting extension of the discussed coordination approaches would be the integration of V2G scenarios where EVs can feed electricity back into the grid (e.g., in times of high prices). This way, the results of Kempton and Tomic (2005) can be investigated in a setting with both uncertainty and grid constraints. Moreover, the current analysis focuses on individual charging behavior. It has often been argued that electrified individual transport may put greater emphasis on vehicle sharing systems (Nair and Miller-Hooks, 2011). Such systems may exhibit greater charging flexibility as requests can be served with the whole fleet which may improve grid integration capabilities.

Chapter 9

Conclusion and Outlook

The integration of very high shares of renewable generation will require significant changes within the power system. Through improved monitoring, forecasting and control capabilities and by empowering the demand side, smart grids will play a key role in addressing this challenge. However, successful establishment of smart grids will require addressing both sound technical and economic concepts. This joint perspective on generating appropriate solutions fuels the convergence of energy informatics and energy economics research. Within this thesis, I explored tools and techniques from both fields to address problems concerning the modeling and coordination of load behavior in future smart grid markets.

The presented results should help generators, system planners and regulators to identify crucial aspects of robust smart grid operation. Among others, these include the benefits of load data availability (from smart metering), the necessity of sufficiently high update frequencies within dynamic pricing schemes, the relative importance of both price and trip information for smart EV charging policies, the trade-off between local (grid constraints) and global coordination goals (load-generation matching) as well as the distinctly spatial dimension of these coordination conflicts.

Given the vastness of this research field, the multitude of challenges and the complexity of any system entity, such work can never be considered finished, completed or exhaustive. Notable omissions have been aspects of decentral generation, transmission grid constraints as well as detailed representation of power engineering aspects. Similarly, my research has only briefly touched on empirical market data and relies on fairly simple coordination approaches such as dynamic pricing or capacity protection. Also the research paths have been fairly isolated with analysis focusing on either EVs charging or residential loads. While this focus was essential for generating compact and coherent results, more overarching conclusion need to be based on more integrated models.

In summary, demand flexibility, market-based integration of renewables, responsive generation as well as hybrid energy systems will create a more diverse (different generation technologies, diverse rate designs, heterogeneous service levels) and consequently more (cost-)efficient and resilient power system. Such a system can dynamically prioritize the different dimensions of the energy trilemma. Consequently, constraints become “softer” which creates a greater set of feasible allocations. For example, selective black-out options provide grid operators with additional emergency reserve capacity — such customized availability level agreements thus allow trade-offs between cost and reliability. Similarly, dynamic (both temporal and spatial) remuneration of renewables can enhance the value of storage capacity and thus provide more effective investment incentives.

Leveraging these future opportunities will not only require appropriate ICT systems for metering and communication as well as economic incentive structures and rates: It will also require appropriate sensor systems and information technology to create smart nodes within a smart grid following the energy informatics paradigm put forward by Watson et al. (2010). These smart nodes can implement decentral optimization and decision-making routines and will constitute intelligent agents within an intelligent system (Ramchurn et al., 2012). Intelligent system design requires meaningful agent models, while meaningful agent models require a system environment to interact with. Therefore, these two aspects are fundamentally interconnected. Consequently, this thesis addressed both the economic design of smart grids (through appropriate population models) and the establishment of smart nodes (through optimization of individual load behavior). It also contributed to the vision of smart markets through discussion of various economic coordination approaches.

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Appendix

Appendix A

List of Abbreviations

AC Alternating Current
AFAP As Fast As Possible Charging Strategy
ALAP As Late As Possible Charging Strategy
ALAP+ As Late As Possible Charging Strategy with price threshold
ALAP-OPT Optimal As Late As Possible Charging Strategy
AMI Advanced Metering Infrastructure
APD Analysis Process Designer
B2B Business-to-Business
BI Business Intelligence
CDF Cumulative Distribution Function
CHP Combined Heat and Power
CRM Customer Relationship Management
CRISP-DM Cross Industry Standard Process for Data Mining
DBI Davies-Bouldin Index
DC Direct Current
DM Data Mining
DR Demand Response
DSM Demand Side Management
DSS Decision Support System
EnWG German Energy Industry Act
EPEX European Power Exchange
ERP Enterprise Resource Planning
ESMR Expected Marginal Seat Revenue
EV Electric Vehicle
ICT Information and Communication Technology
IT Information Technology
KDD Knowledge Discovery in Databases
MIP Mixed-Integer-Program
PARM Perishable Asset Revenue Management
PDF Probability Density Function
PHEV Plug-in Hybrid Electric vehicle
PV Photovoltaic
RLM power-based load measurement
RTP Real-Time Pricing

RM Revenue Management
SAP BI SAP NetWeaver Business Intelligence
SESAM Self Organization & Spontaneity in Liberalized and Harmonized Markets
SGE Smart Grid Economics
SOC State-Of-Charge
TOU Time-Of-Use
V2G Vehicle-to-Grid

Appendix B

Benefits of Demand Side Management

Table B.1: Benefit Estimation Approaches for Demand Side Management Programs (Heffner, 2010)

Source of Benefits	Estimation Approach	Analytic Method
Lower utility costs	Avoided Costing	NPV of utility revenue requirement w/ & w/o a DR program
	IRP	NPV of long-run system costs w/ & w/o DR in the resource portfolio
	Infrastructure Business Cases	NPV of utility fixed and variable operating costs w/ & w/o the infrastructure investment
Lower prices in wholesale markets	Market Price Modeling	Financial impact of a specified DR load impact onprices and power contracts
Improved Reliability	Value of Lost Load	Incremental difference in loss of load value of unserved energy as a result of a DR program
	Option Value	PV of a future option to curtail a given load, constructed to reflect forward energy curves as modified by forecast price & interest rate fluctuations
Lower System and Network operating costs	Network and Transmission Planning Approaches	Improved economic efficiency in the provision of operating reserves and regulation; Reduction in congestion costs and nodal prices; Reduced Cap Ex requirements for peak-related network additions
Environmental Benefits	Environmental cost-benefit analysis	DR impacts on emissions output are calculated (e.g., per unit NOX) & valued based on environmental externality values
Customer Benefits	Consumer Surplus	Consumption patterns adjust in response to higher peak and lower overall prices

Appendix C

Cluster Analysis

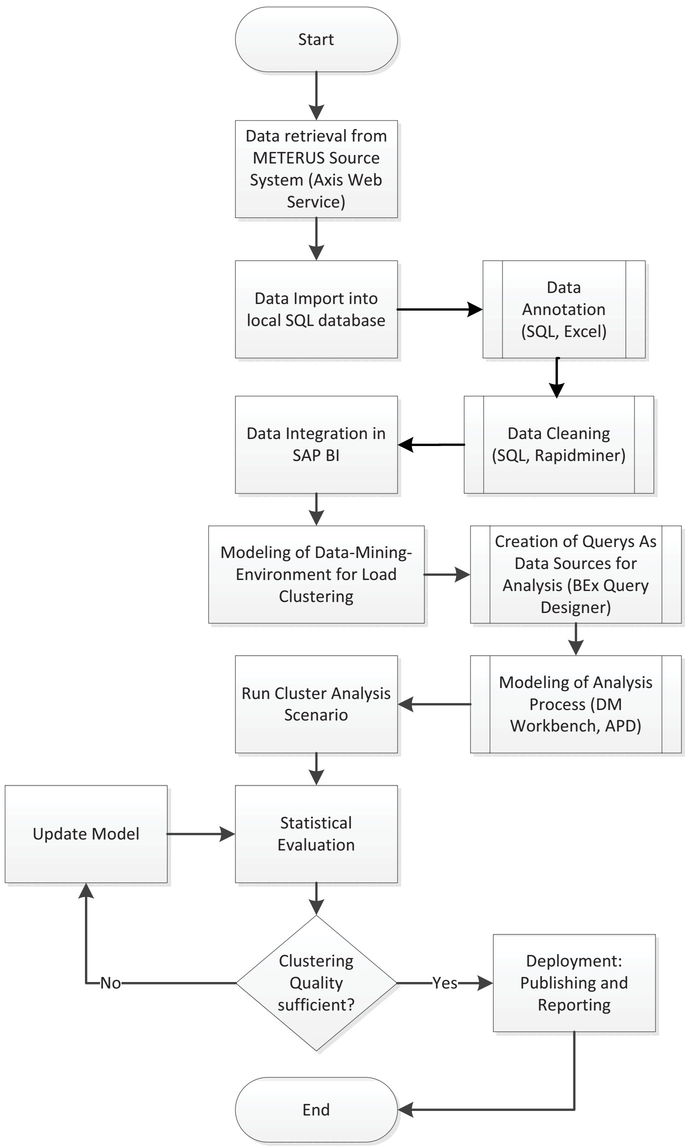

Figure C.1: Overview of KDD process

Table C.1: Additional Cluster Information (workday, winter)

	Cluster Number													
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
Number of customers	8	25	39	25	16	8	12	14	19	18	13	4	13	1
Standard deviation	10.1%	11.1%	10.5%	11.7%	11.8%	10.8%	12.4%	15.8%	10.9%	11.1%	13.5%	7.5%	10.3%	0.00%
Average Consumption	29.0	11.7	11.7	11.9	10.2	9.34	16.9	22.4	15.8	10.8	46.8	47.8	49.7	8.1
Maximum Consumption	161.5	23.8	20.0	21.7	24.1	16.2	59.0	61.1	67.6	21.3	117.6	105.7	85.9	8.1
Minimum Consumption	5.7	4.0	3.6	4.6	3.0	2.3	4.0	2.7	2.6	4.6	15.1	5.6	9.7	8.1
Load Peaks	12:00 19:15	18:45 07:30 11:45	18:30 13:00 07:00	19:15 20:30 13:30	19:30 07:00	07:15 19:45 12:30	11:30 08:15	19:15	18:30 08:00	12:00 18:45	10:30 16:15	05:15	07:15 18:00	06:45 21:30
Early Morning Load Share	9.8%	16.1%	14.2%	11.6%	13.4%	16.1%	16.8%	16.5%	15.1%	13.2%	11.2%	32.4%	28.6%	17.0%
Late Morning Load Share	22.6%	17.7%	14.6%	14.2%	11.6%	14.1%	25.9%	16.3%	15.0%	22.3%	28.5%	4.1%	11.9%	20.7%
Noon Load Share	24.9%	18.1%	17.7%	20.0%	13.0%	22.5%	18.5%	17.0%	16.2%	22.0%	22.9%	5.0%	11.2%	17.8%
Afternoon Load Share	16.5%	17.4%	19.7%	19.7%	16.9%	16.7%	16.2%	16.3%	18.6%	18.4%	25.5%	7.5%	20.2%	16.3%
Evening Load Share	19.0%	21.6%	25.6%	24.5%	33.3%	23.3%	16.7%	17.6%	27.7%	17.7%	8.2%	10.2%	22.9%	20.6%
Night Load Share	7.2%	9.1%	8.3%	9.9%	11.9%	7.4%	5.9%	16.4%	7.5%	6.4%	3.8%	40.8%	5.3%	7.6%

Appendix D

Rate Design

Code D.1 ILOG OPL optimization program for optimal rate design (minimize absolute deviation)

```
/*********************************************
 * OPL 12.5 Model
 * Author: flath
 * Creation Date: 16.01.2013 at 10:49:03
 *********************************************/
int NbPeriods = ...;
range Periods = 1..NbPeriods;
int NbPriceLevels = ...;
float procurementCost[Periods] = ...;
float intercept = ...;
float xi = ...;
dvar float periodPrice[Periods];
dvar float+ positivePriceChange[Periods];
dvar float+ negativePriceChange[Periods];
dvar int negPriceChangeFlag[Periods] in 0..1;
dvar int posPriceChangeFlag[Periods] in 0..1;
dexpr float absolutePriceDifference[t in 1..NbPeriods] = abs(periodPrice[t]-procurementCost[t]);

minimize
sum( t in Periods )
  absolutePriceDifference[t];

subject to
{
ctPriceChangeLimit:
sum( t in Periods ) (posPriceChangeFlag[t]+negPriceChangeFlag[t]) <= NbPriceLevels;

forall(t in 1..NbPeriods-1 )
ctPriceChange:
  periodPrice[t] == periodPrice[t+1] + positivePriceChange[t+1] - negativePriceChange[t+1];

ctPriceChangeLooping:
  periodPrice[1] == periodPrice[NbPeriods] + positivePriceChange[1] - negativePriceChange[1];

forall(t in 1..NbPeriods )
ctPositivePriceChangeFlag:
  positivePriceChange[t] <= posPriceChangeFlag[t]*xi;

forall(t in 1..NbPeriods )
ctNegativePriceChangeFlag:
  negativePriceChange[t] <= negPriceChangeFlag[t]*xi;

  forall(t in 1..NbPeriods )
ctRealChanges:
  posPriceChangeFlag[t]+negPriceChangeFlag[t] <= 1;
}
```

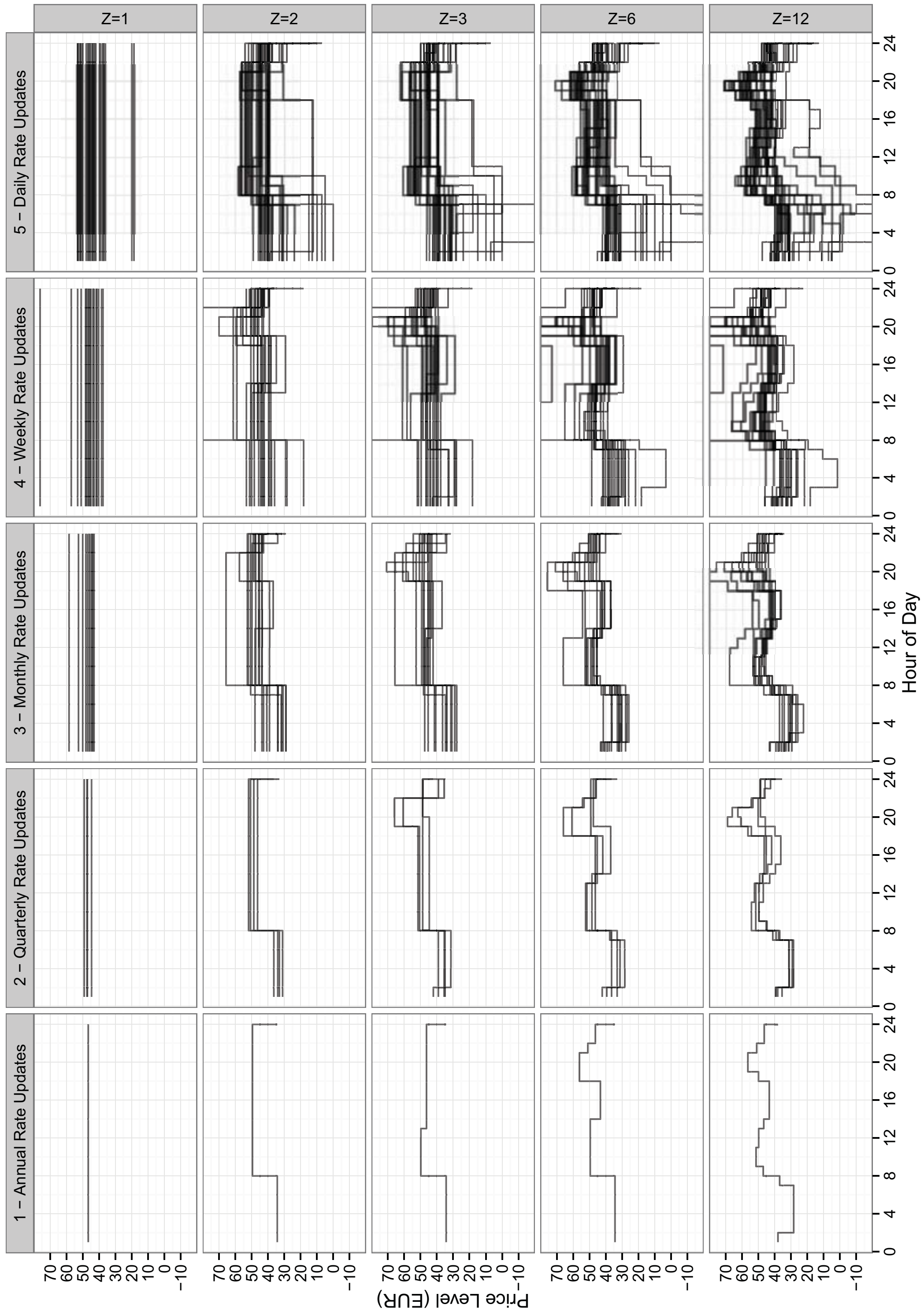

Figure D.1: Visualization of optimal rate structures for procurement cost matching under different updating frequencies and granularity levels with demand-weighted absoluted errors

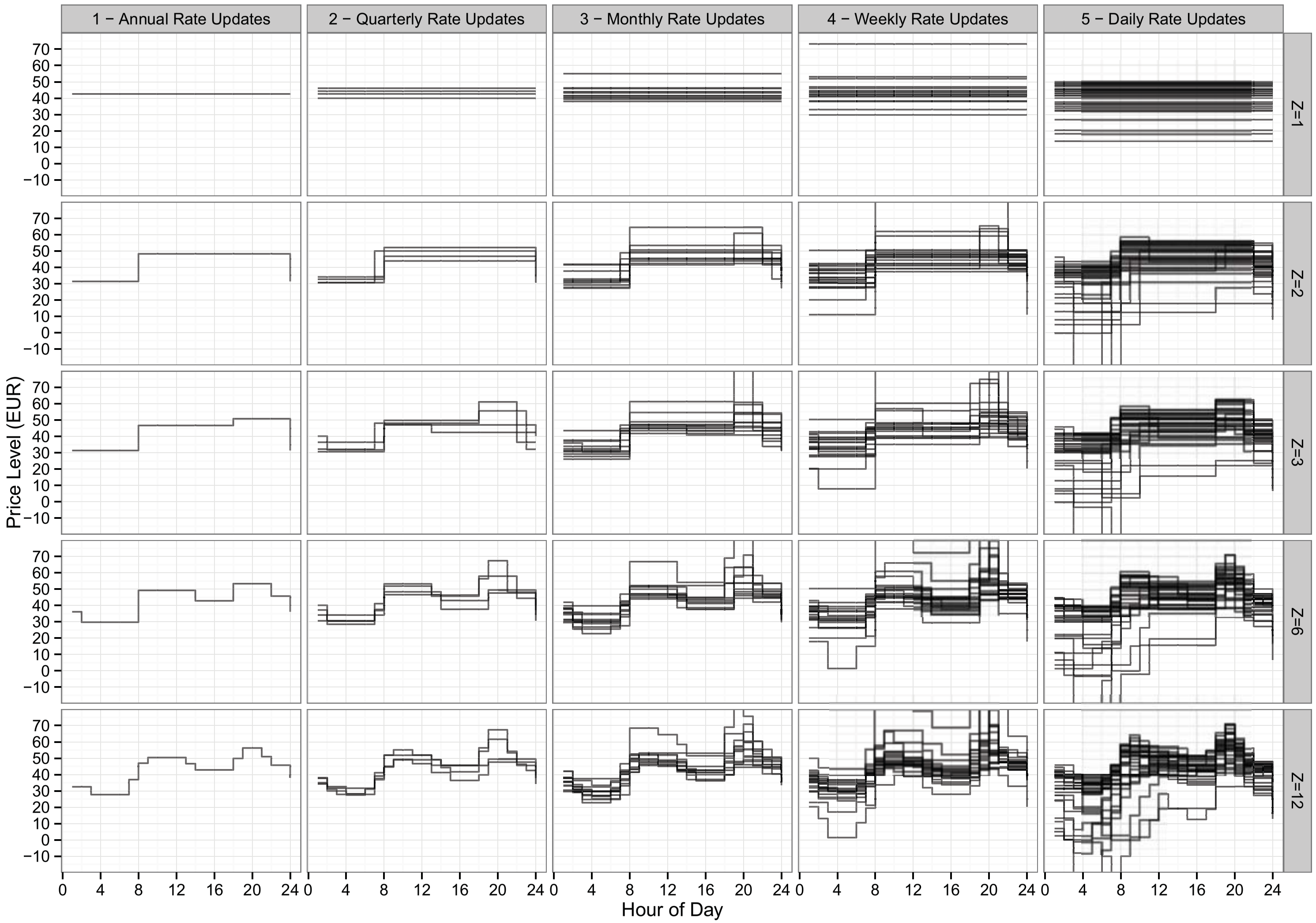

Figure D.2: Visualization of optimal rate structures for procurement cost matching under different updating frequencies and granularity levels with quadratic error weighting

Appendix E

EV Modeling

Table E.1: Overview of abbreviations and model parameters

Scenario parameters	
$\mathbf{c}$	Electricity price vector over time
n	Number of vehicles
γ^i	Vector of consumptions of EV i over time
L^i	Vector of locations of EV over time
ϕ^i	Vector of charging decisions of EV i over time
EV specs and charging behavior	
$\overline{SOC}$	Battery capacity
$\bar{\phi}$	Maximum charging speed
SOC_t^*	Critical SOC level
$\underline{SOC}$	Lower battery threshold
$\underline{c}$	Price threshold
m	Charging granularity
η	Charging efficiency

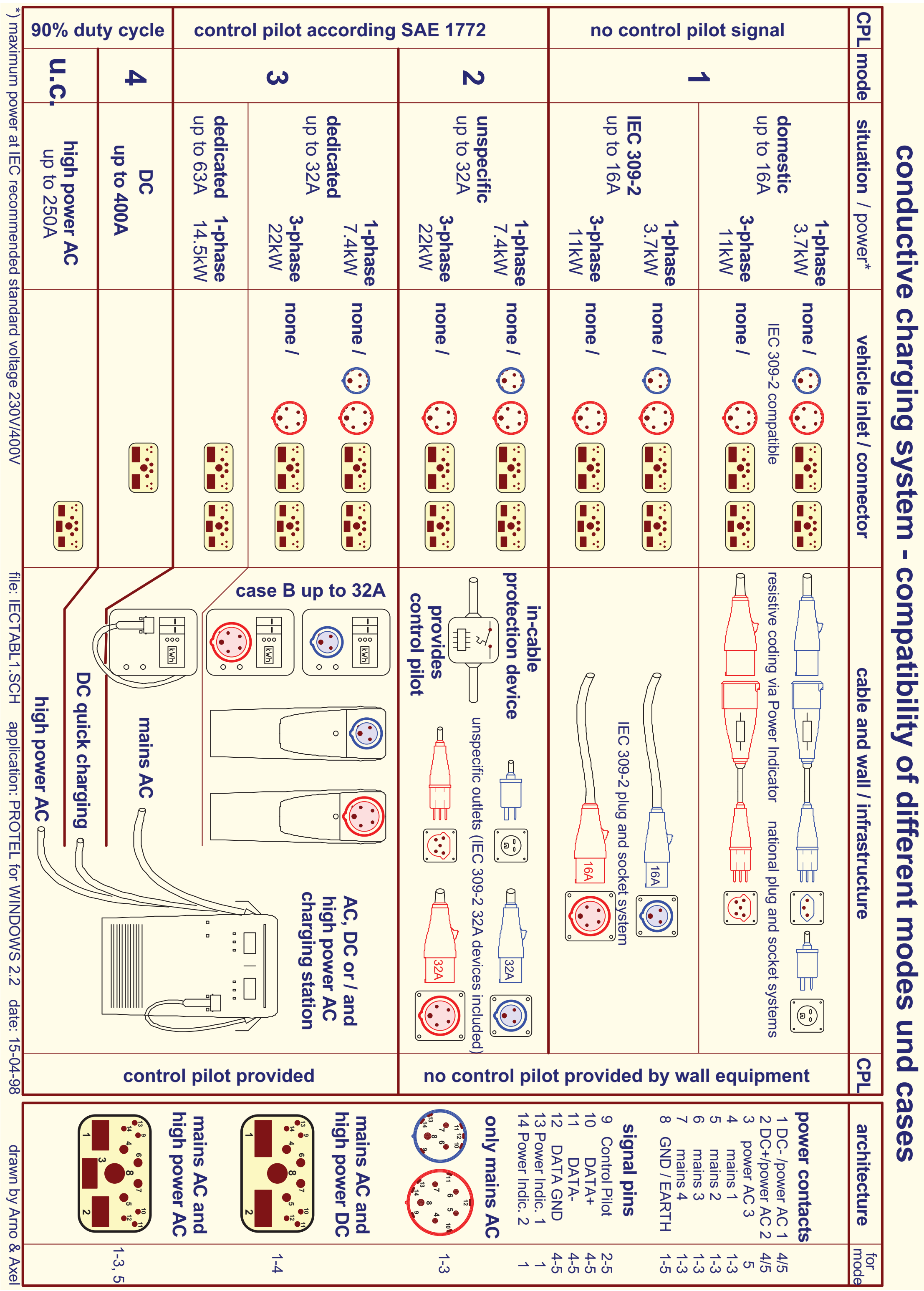

Figure E.1: Annex of IEC 61851-1 (Mathoy, 2008)

Code E.1 ILOG OPL optimization program for optimal smart charging (minimize costs)

```
int NbPeriods = ...;
float initSoc =...;
float maxSoc = ...;
float endSoc = ...;
range Periods = 1..NbPeriods;
float Capacity[Periods] = ...;
float Demand[Periods] = ...;
float Cost[Periods] = ...;

dvar float+ PosChargeamount[Periods];
dvar float+ Soc[Periods];

minimize
sum( t in Periods )
Cost[t]*PosChargeamount[t];

subject to {
forall(t in Periods )
ctNonNegativeSoc:
Soc[t] >= 0;

forall(t in Periods )
ctMaxSoc:
Soc[t] <= maxSoc;

forall( t in Periods )
ctChargeamount:
PosChargeamount[t] <= Capacity[t];

forall( t in 2..NbPeriods )
ctStorageConstraint:
  Soc[t] == Soc[t-1]+ PosChargeamount[t] - Demand[t];

ctInit:
  Soc[1] == initSoc + PosChargeamount [1] + Demand[1];

ctEnd:
  Soc[NbPeriods] >= endSoc;

};
```

Code E.2 ILOG OPL optimization program for optimal smart charging (minimize maximum load)

```
int NbPeriods = ...;
float initSoc =...;
float maxSoc = ...;
float endSoc = ...;
range Periods = 1..NbPeriods;
float Capacity[Periods] = ...;
float Demand[Periods] = ...;
float Cost[Periods] = ...;

dvar float+ PosChargeamount[Periods];
dvar float+ Soc[Periods];
dvar float+ maxLoad[Periods];

minimize
maxLoad[NbPeriods];

subject to {
forall(t in Periods )
ctNonNegativeSoc:
Soc[t] >= 0;

forall(t in Periods )
ctMaxSoc:
Soc[t] <= maxSoc;

forall( t in Periods )
ctChargeamount:
PosChargeamount[t] <= Capacity[t];

forall( t in 2..NbPeriods )
ctStorageConstraint:
  Soc[t] == Soc[t-1]+ PosChargeamount[t] - Demand[t];

ctInit:
  Soc[1] == initSoc + PosChargeamount [1] + Demand[1];

ctEnd:
  Soc[NbPeriods] >= endSoc;

forall( t in 2..NbPeriods )
ctMaxLoadCarryOver:
maxLoad[t]>=maxLoad[t-1];

forall( t in Periods )
ctMaxLoadCurrentPeriod:
maxLoad[t]>=PosChargeamount[t];


};
```

Appendix F

Charging Coordination

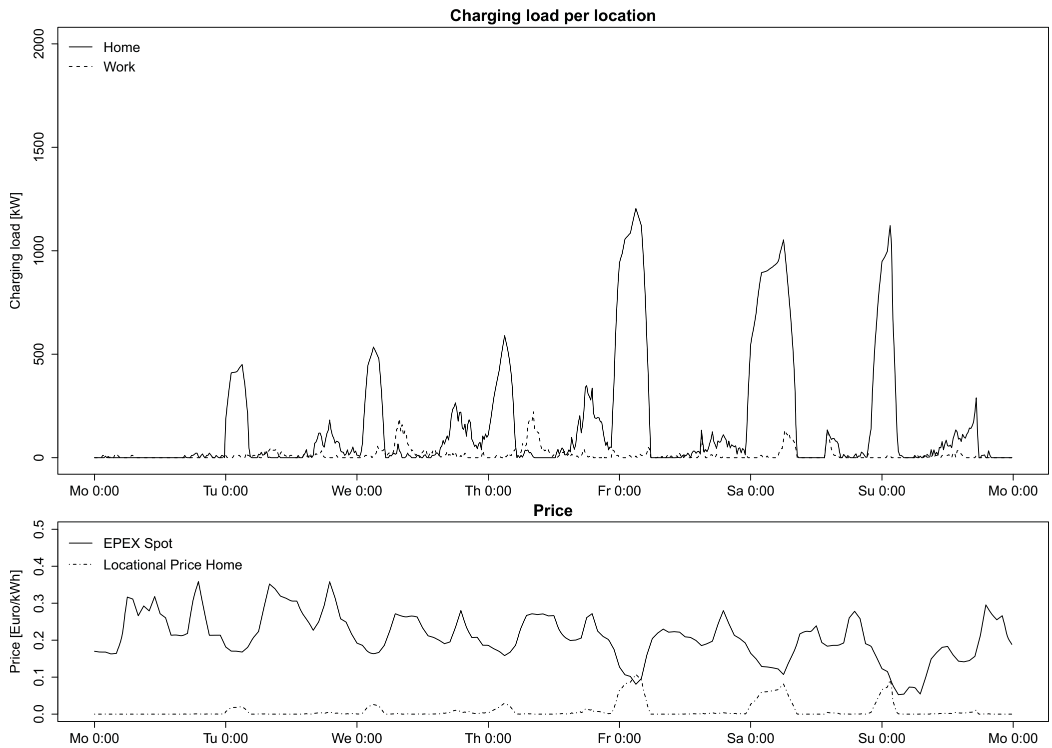

Figure F.1: Aggregate load under heuristic smart charging with area pricing ($\bar{\phi} = 11kW$, $SOC_0 = 100\%$, $SOC_T = 90\%$, $\underline{p} = 0.4$, $\underline{SOC} = 0.3$)

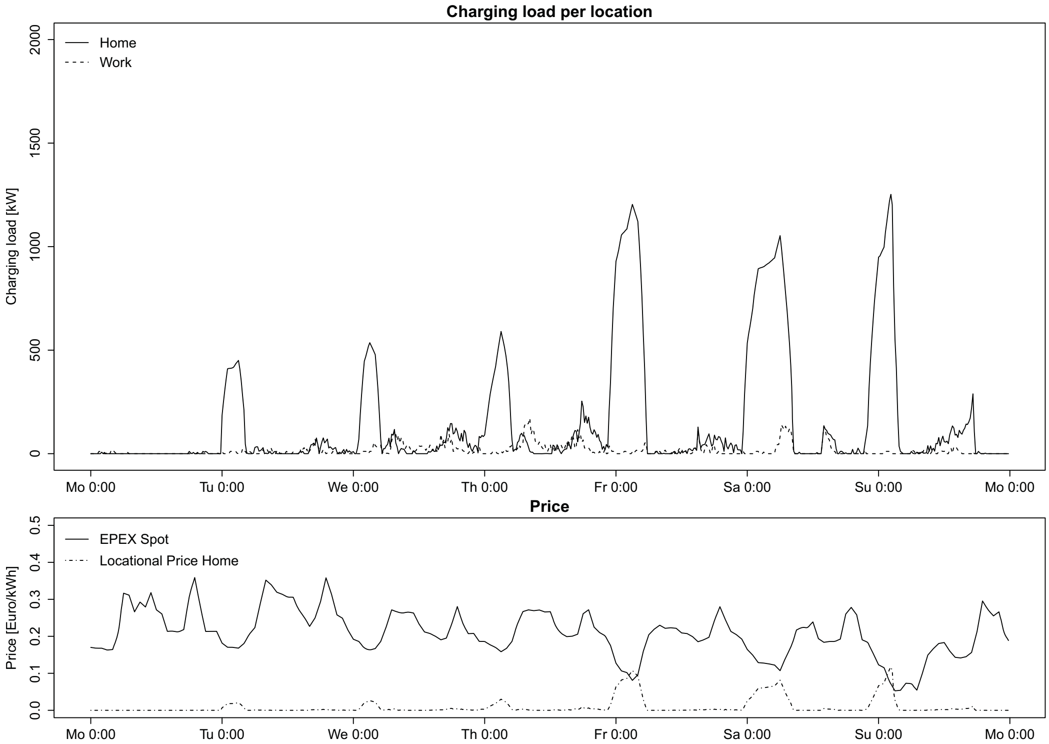

Figure F.2: Aggregate load under heuristic smart charging with area pricing ($\bar{\phi} = 11kW$, $SOC_0 = 100\%$, $SOC_T = 90\%$, $\underline{p} = 0.4$, $\underline{SOC} = 0.15$)

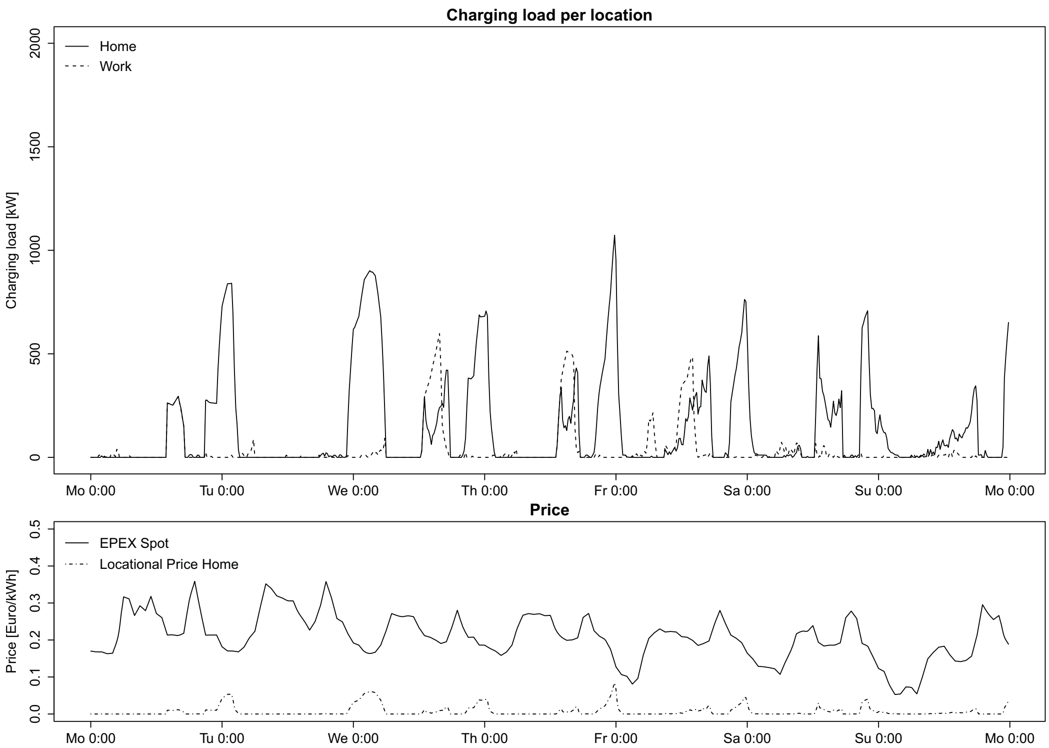

Figure F.3: Aggregate load under heuristic smart charging with area pricing ($\bar{\phi} = 11kW$, $SOC_0 = 100\%$, $SOC_T = 90\%$, $\underline{p} = 0.7$, $\underline{SOC} = 0.3$)