Balancing energy in the German market design

Zur Erlangung des akademischen Grades eines Doktors der Wirtschaftswissenschaften

(Dr. rer. pol.)

von der Fakultät für
Wirtschaftswissenschaften
der Universität Karlsruhe (TH)

genehmigte

DISSERTATION

von

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Tag der mündlichen Prüfung: 30.06. 2010
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2010 Karlsruhe ....

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Chapter 1

Introduction

1.1 Objective

Historically, electricity systems are designed to satisfy a given demand. This paradigm divides the electricity market into a supply-side and a demand-side with a transmission system transporting the electricity from the generator to the consumer. In this view the demand is considered as short term inelastic. The supply-side is categorized into base-load, peak-load and mid-load generation based on a grading of its flexibility in supplying electricity in different aspects of demand.

However, weather dependent renewable generation capacity does not comply with this viewpoint. It contributes to the generation of electricity but cannot be chategorized as base-load, peak-load and mid-load generation. In fact, it is considered as demand-reducing rather than demand-serving generation and may cause negative electricity prices. An increasing relevance of renewables therefore requires a stronger focus on the flexibility in an electricity system and shifts the general approach of producing electricity when needed to consuming electricity when available. With this emphasis on flexibility, all generation and consumption capacity can be grouped into short-term flexible capacity, be it provided by power plants or demand-side-management (DSM), and inflexible capacity. Also, the role of the transmission system is changed to that of a buffer mitigating electricity excess and shortages. This work analyses the central marketplace for flexibility, the *balancing energy market*, in the setting of the German electricity market. In an empirical analysis of the balancing energy demand the following questions are addressed:

- Are there predictable components in the balancing energy demand?
- For what reasons do market participants resort to the balancing energy market?

- To what extend is balancing energy deployed?
- What are the implications of the specific balancing energy market positions on the German electricity market?
- How do these findings relate to the development and harmonization of balancing energy markets in Europe?

Despite their importance for the integration of high shares of renewables in future electricity markets, see for example EU (2008) and U.S.Congress (2009), balancing energy markets are considered as a market of last resort in scientific publications about European electricity markets. This reduces the balancing energy market to a technical necessity and neglects the existence of active positions in the balancing energy market that this analysis proffers.

1.2 Approach

Among European electricity markets the German electricity market stands out as the only major market that does not impose transaction cost or explicit penalties on energy transactions in the balancing energy market. Therefore, it gives the unique opportunity to observe the strategic positions in the balancing energy market and analyze their interplay with other marketplaces. At the same time, the generation stock in the German electricity market that is based on thermal generation, allows to relate the results to many other markets that similarly have a limited flexibility in their electricity system.

In this thesis Germany is regarded as one electricity market, even though its balancing energy market is divided into four control areas. This hypothetical single control area corresponds best to the single German electricity exchange. Also, deviations of different control areas that chancel out and represent no deviation for the total German market do not complicate the analysis. This issue is resolved in netting the balancing energy demand of all control areas. However, the balancing energy prices cannot be combined in the same way because there is no stringent weighting of the four control areas' prices. Therefore, a detailed analysis of balancing energy prices remains beyond the scope of this thesis. Consequently, the analysis is focused on a particular control area, if the balancing energy price is required.

The fundamental approach is to build an econometric model for the total balancing energy demand. In this model the balancing energy demand can be separated into several components that are analyzed separately. However, the components and corresponding strategic positions are derived from a statistical analysis. Therefore, strategic positions are represented by their expectation value, conditional on the historic dynamic of the balancing energy demand. These strategic positions are analyzed with respect to different factors capturing the interplay of the balancing energy market with other marketplaces in Germany.

1.3 Outline

This thesis touches many characteristics of electricity markets and encompasses an econometric analysis of the balancing energy demand. The work is split into two parts. Part I provides an introduction to the specifics of an electricity market, as well as the theoretical background for the concepts and methodologies used throughout the analysis. Part II discusses the approach and findings in the analysis of the German balancing energy demand. It is based on the results of Möller *et al.* (2010), Möller *et al.* (2009b), and Möller *et al.* (2009a).

The presentation in Part I consists of two chapters. Chapter 2 covers the basic concepts of electricity markets. This discussion is complemented by an outline of the general technical components needed in the operation of an electricity system. Concluding the market design of the German electricity market that is in the focus of this thesis is introduced.

Chapter 3 describes econometric concepts of time series analysis. This description is centered around linear time series models and specifically the univariate case. In addition, the distribution of the innovations governing the time series is considered in detail. Finally, both the linear time series model and the innovations' distribution are combined in an outline of a model building approach.

Part II encompasses the analysis of the German balancing energy demand. In Chapter 4 an econometric model for the German balancing energy demand is developed. This model allows the identification and separation of three strategies proffered in this thesis based on the time frame they are deployed. The following discussion maintains this separation and presents the underlying incentives that govern the identified strategies.

The proposed model is than applied to extract the strategic positions in the German balancing energy market for an empirical analysis in Chapter 5. Specifically, the interplay of these strategic positions with two alternative marketplaces the day-ahead market and the capacity reserve market is analyzed. This interplay accentuates the need to consider the balancing energy market on an equal footing with other electricity marketplaces.

In Chapter 6 the main results established in Part II are evaluated in the context of the German electricity market and its projected future development. In particular, the implication of a further harmonization of the

European electricity markets is raised. Finally, recent developments in the German electricity market are reported, which constitute a promising basis for further research and a deeper understanding of the role of balancing energy in a liberalized electricity market.

Part I

Theoretical background

Chapter 2

Electricity markets

Among energy commodities electricity takes a unique role. It practically cannot be stored and its transportation over vast distances is ineffective and expensive. Therefore, electricity markets have to be considered as localized markets and the specifics of individual markets have to be taken into account. In this chapter the basic components of an electricity market are introduced and an overview of the mechanisms implemented to ensure efficient functioning of these components is given. The presentation is focused on the analysis in this thesis and therefore concentrates on the German market. The terminology introduced in this chapter and used throughout the thesis keeps to the terminology used in the handbook of the union for the coordination of transmission of electricity (UCTE). For further reading refere to Eydeland and Wolyniec (2003), and Geman (2005).

Historically, electricity markets have been highly centralized and were often centered around one public owned monopolistic player. These players were characterized by vertical integration, controlling every aspect of the electricity market. By the end of last century more and more countries started to liberalize their electricity markets. Thus transforming the monopolistic vertically integrated market into a competitive marketplace for diverse and specialized players. This liberalization increased the necessity to understand and model the behavior of the electricity market. Particularly, this holds for the market participants that are exposed to newly unfold inner market risks. Additionally, regulators and the increasing interaction between financial markets and electricity markets drive model development and academic interest.

2.1 Basic concepts of electricity markets

Electricity is mediated by electro-magnetic fields that propagate at the speed of light and cannot be stored efficiently. Therefore, the equilibrium of supply and demand is a key aspect of electricity, as it has to be maintained dynamically at every instant. In fact, a black out being a static zero equilibrium will be initiated to protect the infrastructure, if a dynamic equilibrium cannot be maintained.

The following sections present basic concepts along the line of the traditional division into supply-side and demand-side. These concepts are fundamental for an understanding of the operation of electricity markets.

2.1.1 Electricity demand

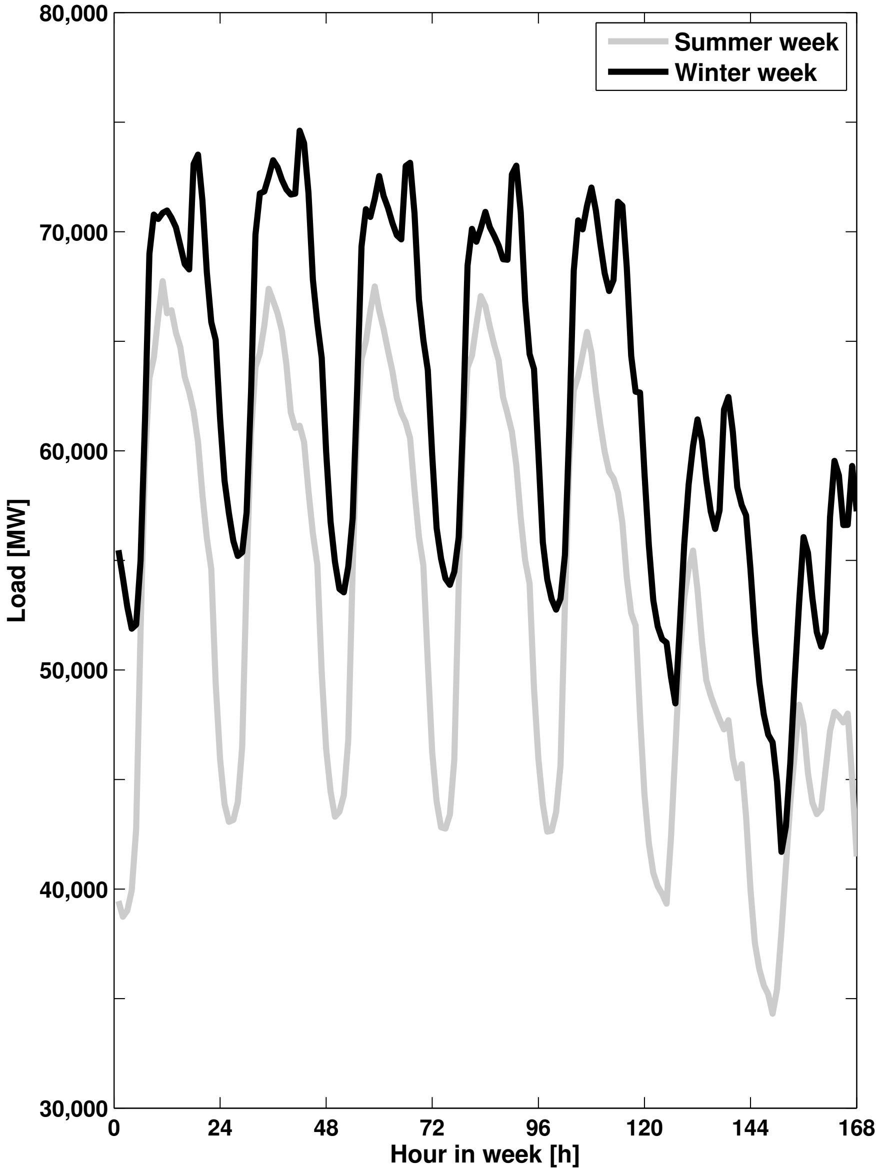
The consumption of electricity is omnipresent in modern life, and is continuing to gain importance as indicated by ever growing electricity demand. It ranges from small household applications to large-scale industrial applications. Naturally, electricity demand therefore follows the same cyclical patterns as modern life. Thus, electricity demand shows the same seasonality of day-time and night-time, weekday-day and weekend and summer and winter. Figure 2.1 demonstrates this seasonality with the example of the German electricity demand. The data shown is taken from two weeks in 2006. The summer-winter seasonality creates an offset between the summer and the winter demand curves because heating and lighting induce an additional demand. The periodical change form low night-time to high day-time demand is obvious in both curves. Also, the difference between the first five and the sixth and seventh weekday cycle can easily be identified. A closer inspection of the week-day cycles reveals an additional hump during evening hours that is only present in the winter week, and marks another manifestation of the summer-winter cycle. Additionally, this example demonstrates how an electricity market is influenced by local specifics such as the demand profile. By comparison, the demand profiles of Scandinavia with a more pronounced heating demand in the winter, or California with high cooling demand in the summer, each lead to their own respective seasonality.

Flexible demand

Typically, electricity demand is considered as short-term inelastic. For one consumers do not reconsider their use of electricity each time they use it. Even if they did, they do not respond to short-term information because consumers are usually supplied by long-term contracts. From this point of view, the supply-side of the market has to account for all the flexibility to keep the electricity system in an equilibrium state. In general, this is a valid assumption. However there are some exceptions.

Pumped-storage facilities are a widely used example of flexible demand.

Figure 2.1: Weekly load pattern (Monday to Sunday) in summer and winter



They extend the flexibility of hydroelectric dams by reversing the direction of flow. During periods of low demand electricity is used to pump water into a reservoir. This power can than be released during periods of high demand. Naturally, pumped-storage facilities are electricity consumers that are overall using electricity to produce electricity. Also other physical and chemical forms of energy storage are considered to provide flexible demand. Up to now however, these processes do not reach the efficiency of pumped-storage and play only a minor role.

In general, a great variety of industrial processes such as aluminum electrolysis or cold storage houses have the potential to implicitly store energy by diverting electricity consumption to a time of lower demand. Such demand alterations are subsumed in the so-called *demand side management* (DSM), and can be extended even to minor household appliances such as a fridge. Obviously, DSM relies heavily on the flow of information and on adequate process control. This so-called smart grid is not implemented in the German market on a significant scale.

2.1.2 Electricity supply

The discussion of electricity demand in the previous section marks demand as dynamic. Taking into account the influence of external factors as the weather, electricity demand is evidently not entirely predictable. Considering all the unpredictable events that influence electricity demand — including human behavioral patterns — gives an indication of the flexibility needed on the production side of the market to meet this dynamic demand and guarantee the instantaneous equilibrium of supply and demand. This flexibility is created by a diverse generation stock with the exact generation mix reflecting the economic, geographic and political conditions of a specific market.

In general, it is helpful to divide the generation stock into three groups reflecting the kind of demand served. The groups are the so-called *base-load, peak-load and mid-load units*. Base-load units are designed to generate electricity as cheap as possible. They are operated to cover the consistent fraction of electricity demand that does not vanish even during the off-peak periods at nights or weekends. Thus, the design allows for a high degree of technical sophistication that amortizes with the units' usually large capacity and over the many operating hours. Therefore, base-load units are characterized by high fixed cost and low variable cost. Naturally, output alterations play little role in the design of base load units, and they are therefore inapt to counter the changes in demand. In contrast, peak-load units are designed to be as cheap as possible to generate electricity during periods of high demand. Peak load units often have a small capacity, which increases the flexibility of their use. The design focues on minimal fixed cost of peak units and brings about high variable cost that lead to a steep price increase during periods of peak demand. The third group of units are the so-called mid-load units. They are operated to counter the cyclic changes between day-time and night-time demand. These regular operating hours allow for the amortization of some technical sophistication in the design. Cyclic units combine moderate fixed cost with moderate variable cost and fill the gap between base-load and peak-load units.

The variable cost of all generation units can be ordered based on the variable cost. This ordering results in the so-called *merit-order-curve*. It ranges from low merit-order base-load to high merit-order peak-load units. In a perfectly competitive electricity market the value of the merit-order-curve at a given period's demand is the price of electricity for that period. See Figure 2.2. This relationship helps to understand the seasonality of electricity prices and, considering the non-linear shape of the merit-order curve, the extreme price changes common in electricity markets.

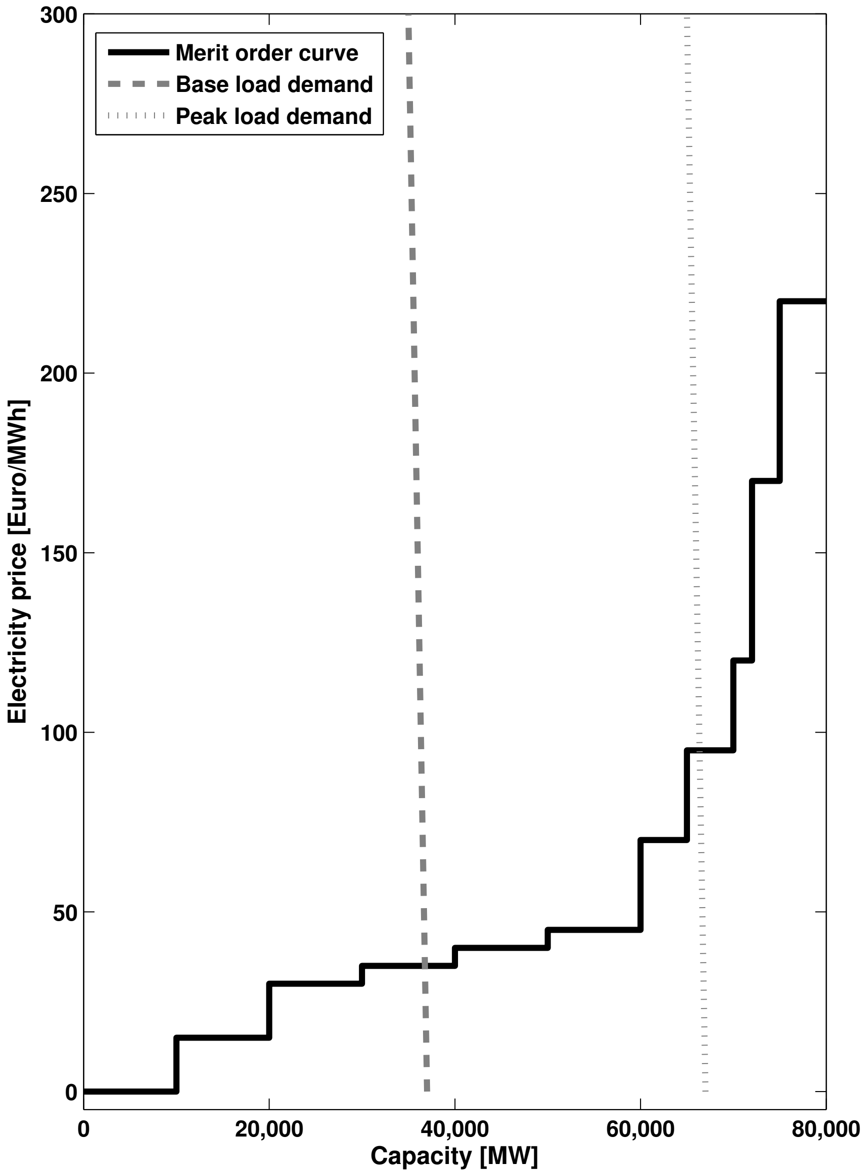
In the following different types of generation are introduced and characterized in the context of this work with a focus on the German electricity mix.

Conventional thermal and nuclear

Conventional thermal and nuclear power stations are designed to convert the heat of some heat source into steam, which in turn drives a turbine that generates electricity. They can easily be categorized into one of the three groups based on the targeted load spectrum because they are designed with respect to a specific niche. On the base-load end of the spectrum are nuclear or lignite power plants that tap cheap sources of energy at considerable technical expense. Also, the installed capacity of such units tends to be large due to efficiency of scale considerations. Coal power plants are often designed as mid-load units, though some coal fired plants are also operated as base-load units. Thermal peak load plants are often fired by natural gas. However, modern combined cycle technology gas fired plants are also competitive as mid-load units. Concerning liquid oil based fuels, the electricity sector is in competition with the transportation sector leading to unattractive fuel prices. Therefore, these fuels only play a minor role in the German market. (See BDEW Bundesverband der Energie- und Wasserwirtschaft e.V. (2009).)

The combined heat and power *CHP* technology greatly increases the efficiency of fuel usage. Such units have to be operated under the additional constraint of heat demand. Therefore, these units are suited as the base-load

Figure 2.2: Merit-order curve of a hypthetical electricity market



and mid-load units only and are operated outside merit-order at times.

Renewables

In contrast to conventional power stations, renewable power is designed to tap a given energy source rather than serveing a given demand profile. In addition, renewable energy has to follow the natural fluctuations in the availability of the used energy source. Therefore, it is often helpful to consider renewables as demand reducing rather than demand serving units.

Hydroelectricity is a well established form of renewable electricity generation. It can be subdivided into run-of-the-river and dam sites. Run-of-the-river units have to utilize the hydro power as it arrives and consequently reduce the base-load in lock-step with the water flow. In contrast, hydroelectric dams utilize the storage capacity of the reservoir and also serves the more profitable peak-load.

Like run-of-the-river units, wind turbines reduce the demand, as the wind energy cannot be stored directly. However, wind speed is dependent on the time of day. Thus, statistically wind turbines also partially reduce peak demand. (See von Roon and Wagner (2009) and Oliver and Zarling (2009).) Nonetheless, the availability of wind power is subject to large fluctuations that the electricity system has to compensate.

Solar energy obviously follows a peak-load production pattern. However, despite technical advances solar-thermal and photovoltaics only contribute marginally to the German electricity production.

In contrast to wind and solar power, biomass is a freely deployable renewable energy source. Biomass is thermally converted into electricity, either directly or via gasification in a biological or chemical process. The gasification process is operated continuously, but in combination with adequate storage infrastructure, biomass can contribute to the flexibility needed to balance demand fluctuations.

2.1.3 Electricity network

Electricity supply and demand are connected by the electricity network. This network serves two basic needs. First, electricity has to be transported over distances by the transmission system and than onward to all the individual consumers by the distribution system. Second, the network serves as a buffer balancing all fluctuations that occur. All suppliers and consumers are connected synchronously, i.e., everyone physically connected to the network is directly affected by fluctuations and directly affects everyone else. Therefore, fluctuations in the network have to be actively controlled and kept within a certain bandwidth. Should this bandwidth be violated a black-out has to be initiated to protect the infrastructure from damage.

The operation of the network is entrusted to a single player in a given region, the so-called transmission system operator (TSO). Even in liberalized markets the TSO is organized as a monopolistic player. This concentration of responsibility reduces the overall control interventions necessary. By aggregating all fluctuations at the highest possible level, off-setting fluctuations cancel and do not need to be controlled. Therefore, a single TSO incurs less cost than active balancing of several sub-entities.

The flexibility to control fluctuations is expensive. It is therefore more efficient to replace the most flexible intervention measures with a less flexible and less expensive one. It is common to group response measures into the following three categories:

Primary reserve The primary reserve or spinning reserve automatically reacts to changes in the load. A load change results in a phase shift between grid frequency and spinning turbines in effect initiating the necessary energy adjustment. In order not to stall the power plants, automatic control detects these changes and alters the plant power operation accordingly. Plants participating in primary control have to keep operational margins, i.e., a plant that can operate from 70% to 100% installed capacity may only be operated between 80% to 90% installed capacity to keep sufficient reserve in either direction. Primary reserve capacity is limited and expensive. If not released by an offsetting fluctuation in the network, it should therefore be released by secondary reserve. Calling secondary reserve results in an offsetting load change and the automatic control brings the primary control plants back to their initial operating point. Primary control covers load changes for a time frame of the order of minutes. The energy output of participating power plants does not change on average because secondary reserve releases primary reserve capacity by innitiating an offsetting load change. Therefore, primary reserve is compensated entirely based on capacity payments, as effectively no additional energy is delivered or consumed.

Secondary reserve While primary reserve covers small fluctuations that are by all likelihood canceled by another fluctuation; secondary reserve covers unforeseen events. A provider of secondary regulatory power has to satisfy a TSOs' demand for up or down regulation within several minutes. Usually, this time is insufficient for start up or shut down, so secondary regulation is served by adapting the operational state of running production or consumption capacity. As secondary reserve implies the exchange of energy, secondary reserve has prices for both reserving capacity and the actual energy delivered. A system can be operated entirely on primary and secondary reserve. However, it might be cheaper to replace secondary reserve with yet another level of reserve, the tertiary reserve.

Tertiary reserve In general, the tertiary reserve is not different to the secondary reserve, other than in its response time. It is used to cover the risk of big and long lasting events such as a forced outage of a nuclear power station. As these events are rather rare and response time constraints are less rigorous, tertiary reserve can be served by technically less advanced facilities, opening the market of regulatory energy to a wider category of providers. Potentially, this lowers the cost of balancing energy. Like in the case of secondary reserve, the cost of tertiary reserve include both capacity payments and payments for the exchanged energy.

In addition to the balancing of fluctuations, there are other factors the TSO has to monitor that are closely related. The network has to be provided with sufficient supply and transmission reserves to compensate fluctuations. Specifically, it has to be ensured that the electricity flow keeps to the physical limitations set by the transmission capacity. This involves planning the electricity flow in the network in advance and initiating necessary adjustments. It is further complicated by the interaction with other networks through non-synchronous direct current interconnector lines that have to be planned as prodution or consumption units depending on the direction of energy flow. These tasks reinforce the importance of a single responsible TSO. However, in the context of this thesis the TSO is reduced to the tasks of controlling fluctuations, the procurement of capacity reserve, and a precise metering of all suppliers and consumers that is used to settle possible energy transactions evoked by fluctuations.

2.2 Marketplaces for electricity

The design of a liberalized electricity market provides several marketplaces that are linked to different aspects introduced in Section 2.1. The following discussion of these marketplaces is organized along the time line, from long before to after the actual delivery and consumption of electricity. It is also focused on bilateral markets. This is the common European market design and constitutes a further step in liberalization as compared to the alternative pool market design with a monopolistic buyer.

2.2.1 Futures market

Electricity futures are traded long before the actual delivery of the traded electricity. Typical delivery periods range from one year to a week. The contracts specify a constant delivery of electricity over the entire delivery period. Therefore the cash flow of a futures contract is equal to the average electricity price during the delivery period. Futures correspond to the long-term planning needs of market participants, for example those that need to hedge the risk of large investments such as a base-load power plant.

To account for the seasonality of electricity demand within the delivery period futures are often designed as base-load and peak-load futures. The peak-load contracts aggregate the hours of high seasonal demand, in contrast to 24/7 delivery of base-load contracts. With a combination of these contracts typical production and consumption patterns in the electricity portfolios can be roughly approximated and hedged.

2.2.2 Day-ahead market

At a time close to delivery more detailed information is available and market participants can predict their electricity consumption or production more accurately. From the perspective of network operation this information is vital in planning procedures as it indicates the expected electricity flows in the network. Market participants are therefore urged to balance any open position in their estimates. This fine tuning of portfolios is achieved on the day-head market. The day-ahead market practically offers a selection of futures contracts with — depending on the market — hourly or half-hourly delivery periods. These contracts allow for a much more accurate approximation of portfolios and many market participants use this market to finalize their positions. Therefore, the day-ahead market is also referred to as the spot market.

In fact, the clearing price of the day-ahead market is often used as a reference price in other contracts, as financially settled futures. The prices reflect the information of the merit-order-curve known 24 hours ahead with a given time resolution of one hour or half-hour. In the event of a scarcity the day-ahead market prices tend to the extreme and a price ten times the average level is not rare. This behavior can be attributed to the non-storable character of electricity and an inelastic demand. Therefore, the day-ahead market has a central role in the electricity market because it incorporates all relevant information and serves as a price reference.

2.2.3 Intraday market

After the day-ahead market is closed some markets allow for further adjustments of portfolios in an intraday market. However, compared to the day-ahead market this market has a lower liquidity. Market participants can use this market to incorporate new information affecting their portfolio. At some point in time the so-called *gate-closure* the trading is stopped. The remaining time is needed for the TSO to aggregate all portfolios and ensure this aggregation is compatible with operational constraints. The intra-day market is most relevant for market participants with positions often affected by events between day-ahead market and gate-closure. However, it usually does not reach the liquidity of the day-ahead market.

2.2.4 Capacity reserve market

After the gate-closure the planned electricity consumption and production should be in equilibrium. However, despite all planning efforts the electricity system will always be affected by unforeseen events. As discussed in Section 2.1 reserve capacity is allocated by the TSO in advance to account for such deviations between the true electricity flow and the electricity flow scheduled at gate-closure. Capacity reserve is rewarded by a capacity premium because the energy demand due to this deviations is uncertain. In addition, prices for the net energy flow are specified.

The duration of corresponding contracts for reserve capacity dependents on the type of reserve capacity —primary/ secondary/ tertiary— but commonly exceeds the duration of day-ahead market contracts. Therefore, the capacity reserve market does not fit into the concept of presenting the different markets along the time line as contracts are closed at the same time as in the futures market. However, capacity reserve represents the ex ante view on the fluctuations that occur after gate-closure, which places the capacity reserve market on the time line between intraday and balancing energy market.

2.2.5 Balancing energy market

Balancing energy is the ex-post view on the fluctuations that occur after gate-closure. It refers to the settlement of the net deviation of market participants due to fluctuations in a specified balancing period. Often the balancing periods coincide with the periods traded on the day-ahead market. In the balancing energy market the cost caused by energy fluctuations is apportioned to the market participants causing a fluctuation. The main price setting criteria is the net deviation of all market participants. Naturally, balancing energy is expensive when there is a shortage of electricity and inexpensive during balancing periods with an oversupply.

The TSO takes a central role in the balancing energy market in many ways comparable to the mediating position of an exchange. All other market participants are organized in a so-called balancing responsible party (BRP) that settles its fluctuations with the TSO. The TSO meters the energy flow for each BRP and compares it to the energy scheduled by the BRP at gate-closure. A BRP having consumed electricity relative to its forecast then pays the TSO for this energy, while a BRP having feed in electricity relative to its schedule is compensated by the TSO. In the following a sign convention is used where a positive deviation denotes electricity consumption by a BRP relative to it schedule. A negative deviation denotes electricity supply relative to the schedule.

It is important to note that the balancing energy market serves two main objectives. First, it is designed to settle the inevitable fluctuations that occur due to unpredictable events. The sum of such fluctuations should be kept minimal because accidence of fluctuations that can be managed by the TSO results in a black-out. Second, the balancing energy market is central in mitigating the adequate preliminary schedule for the real-time operation of the electricity system. In this respect all transactions in marketplaces up to the gate-closure in the intra-day market are a means of composing the preliminary schedule. The value of this preliminary schedule with respect to the physical transactions of electricity is than determined in the balancing energy market.

In the context of energy transactions in the balancing energy market two basic schemes for the settlement of fluctuations can be distinguished: the single-price settlement scheme and the dual-price settlement scheme. In the single-price settlement scheme the TSO sets one price for each settlement period. All BRPs with a positive deviation pay this balancing energy price for their deviation, and all BRPs with a negative deviation are compensated based on this price.

In contrast, the TSO sets two prices for each settlement period in the dual-price settlement scheme. BRPs being supplied by the TSO pay the price for positive deviations, while BRPs with a negative deviation are reimbursed another price for their energy delivery. In effect, this can be understood as the single-price scheme with an additional transaction cost to discourage speculation. In fact, markets with a dual-price settlement scheme often have an explicit penalty for transactions in the balancing energy market.

The design of the balancing energy market varies among electricity markets, reflecting a different weighting of the two main objectives. Some markets organize the balancing energy market as a real-time market. The TSO constantly informs market participants about the price, thereby allowing them to adjust their preliminary schedule if feasible. In contrast, prices are set after the actual occurrence of a fluctuation in European electricity markets. In particular, they are therefore unknown at the initiation of a position in the balancing energy market. The European balancing energy markets differ in the transaction cost and —if applicable— in the explicit penalties that are levied on transactions in the balancing energy market. An effect of these cost is a transition from a cost reflective preliminary schedule, to a preliminary schedule with a fixed zero position in the balancing energy market to avoid transaction cost. This zero-position preliminary schedule characterizes a strong focus on network security, and disregards any alternative secure schedule. The discussion of such alternative secure schedules is taken up in Part II. For a further discussion of different market designs refer to Zhou *et al.* (2003), EU (2005), and Nordel (2008).

2.3 German electricity market

The details of electricity market designs are diverse, and necessarily reflect local specifics as generation stock or customary operation policies. Due to the limited interconnecting transmission capacity between control areas, the report by ETSO (2007) sees this diversity prevailing in the future. At the same time a great potential is seen in the harmonization of balancing energy mechanisms. (See ERGEG (2006)). This section introduces relevant details of the German electricity market that is in the focus of this thesis.

The German market design is particularly suited for an analysis for two main reasons. First, the German balancing energy market does not impose transaction cost. Consequently, its interplay with other markets can be observed without such distortions. Second, the German balancing energy market has a shorter settlement period than the respective day-ahead market. Thus, the interplay of balancing energy and day-ahead market can be neglected on the sub-hourly time frame, allowing a direct comparison to the capacity reserve market. In general, the results of the analysis are applicable to a wide range of markets with a comparable thermal-based generation stock that are characterized by a high value of flexible generation capacity.

2.3.1 Generation stock

Germany has a diverse generation stock and does not rely on any particular type of generation to more than 25%. The base-load is primarily covered by nuclear and lignite power plants that account for about 23% of German electricity production each. Coal burning power plants account for another 20% of generation, serveing predominantly cyclic demand. Natural gas is the third important fossil fuel and is predominantly imported from Russia and the North Sea. Natural gas fired power plants serve peak-load demand and account for 13% of production. Both natural gas and coal power plants often employ CHP technology, roughly 50% of natural gas electricity production and 25% of coal electricity production stemming from CHP power plants. In total 15% of German electricity is produced with CHP technology. (See BMU (2009))

The renewable sector contributes 15% to the German electricity consumption. Among the renewables wind turbines take the largest share, generating 6.5% of the electricity consumed. Biomass and hydro also take a market share of over one percent, serving 4.5% and 3.4% respectively. (See BMU (2009).)

The remainder of the electricity generation is contributed by marginal sources like pumped-storage, oil based thermal and photovoltaics. Germany is also strongly interconnected with neighboring countries. However, these interconnections are used for both imports and exports of electricity. Overall the interconnections amount to an electricity export. It should be noted though, the usage of interconnections varies strongly and it is therefore not possible to characterize interconnection lines as a strict supply or demand factor. Appendix D.3 gives an quantitative overview of the elctricity supply and demand in the analyzed time period.

2.3.2 Marketplaces

Electricity exchange

Germany has a liberalized electricity market that is based on bilateral contracts between market participants and a large fraction of transactions is settled in over-the-counter (OTC) trades. However, the prices at the European energy exchange (EEX) often serve as a price reference for these contracts. Therefore, the EEX can be regarded as the central German marketplace, despite its relatively small market share of about 15% of German electricity consumption. (See Michalk (2008).) Hence, in this analysis the day-ahead market serves as the reference market the balancing energy market is linked with.

The standard products traded at the EEX are hourly day-ahead contacts as well as bundled base and peak contracts. The closing prices of the hourly contracts are published in the so-called Phelix index. Monthly base and peak futures are written on the average Phelix price of the corresponding hours as the underlying. Additionally, year and quarter futures are available that are cascaded down — via quarter futures — to month futures. Electricity futures have a maturity of up to six years at the EEX. Futures are settled financially at the EEX. However, holders also have the option to expand to physical delivery. The EEX then automatically sets market orders for the corresponding hours of the futures contract.

Since 2006 the EEX also operates an intra-day market based on the same hourly contracts traded in the day-ahead market. It has a gate-closure of 75 minutes prior to the hour of delivery. European Energy Exchange (2010)

Capacity reserve

Naturally, in the capacity reserve market the TSO as the single buyer takes a central role. In the particular case of Germany the electricity system is operated in four control areas by four independent TSOs shown in Figure 2.3. These four TSOs organize auctions for their reserve capacity allocation, which used to be independent but were combined to joined auctions later. In both cases, the location of a particular bidding installation is incorporated in the auctions to account for possible restrictions.

Primary and secondary reserve is allocated in contracts that span over longer periods of time. These periods used to be half a year but were changed to one month. Tertiary reserve is allocated in day-ahead auctions in fractions of four hour periods of the following day. Compared to the hourly day-ahead contracts the averaging periods of the secondary and tertiary reserve are longer. Consequently, the prices cannot respond to short-term supply shocks in the same way. This is an important point that is developed further in Part II of this thesis.

It is important to recall that primary reserve is deployed in a way that ensures a total of zero energy exchange. Therefore, it is compensated by capacity payments only. In contrast, secondary and tertiary reserves imply an energy exchange when called, so in addition to the capacity payment an energy price is fixed for these contracts. Due to the importance of capacity reserve for system stability, the TSOs set technical standards for the authorization of facilities to the capacity reserve market. These standards establish response-time and reliability requirements for the different types of reserve. In general, the requirements are readily met by power plants, while they impose a considerable entrance barrier for DSM capacity. Therefore, the capacity reserve market auctions are dominated by the supply-type bidders. Information on the organization of the capacity reserve market auctions of the four TSOs is joinedly presented at regelleistung.net (2009).

Balancing energy

The cost generated in balancing fluctuations is passed on from the TSO to the BRPs. All four German TSOs use a single-price balancing energy settlement scheme in combination with quarter-hourly settlement periods. Thus, the settlement scheme implyes no transaction cost. Roughly, the balancing energy price is four to five times the average day-ahead market price during periods with a positive net deviation of the control area, and zero during periods with a negative net deviation. Also, it is important to note that the price is set by the TSO after the occurrence of a deviation based on the cost incurred during a particular balancing period. In turn these cost reflect the energy prices of secondary and tertiary reserve deployed in the respective period. Despite the uncertainty of the price, it is still financially beneficial for a BRP to deviate contrary to the net deviation of the control area on account of the high price spread between periods with positive and negative net deviation.

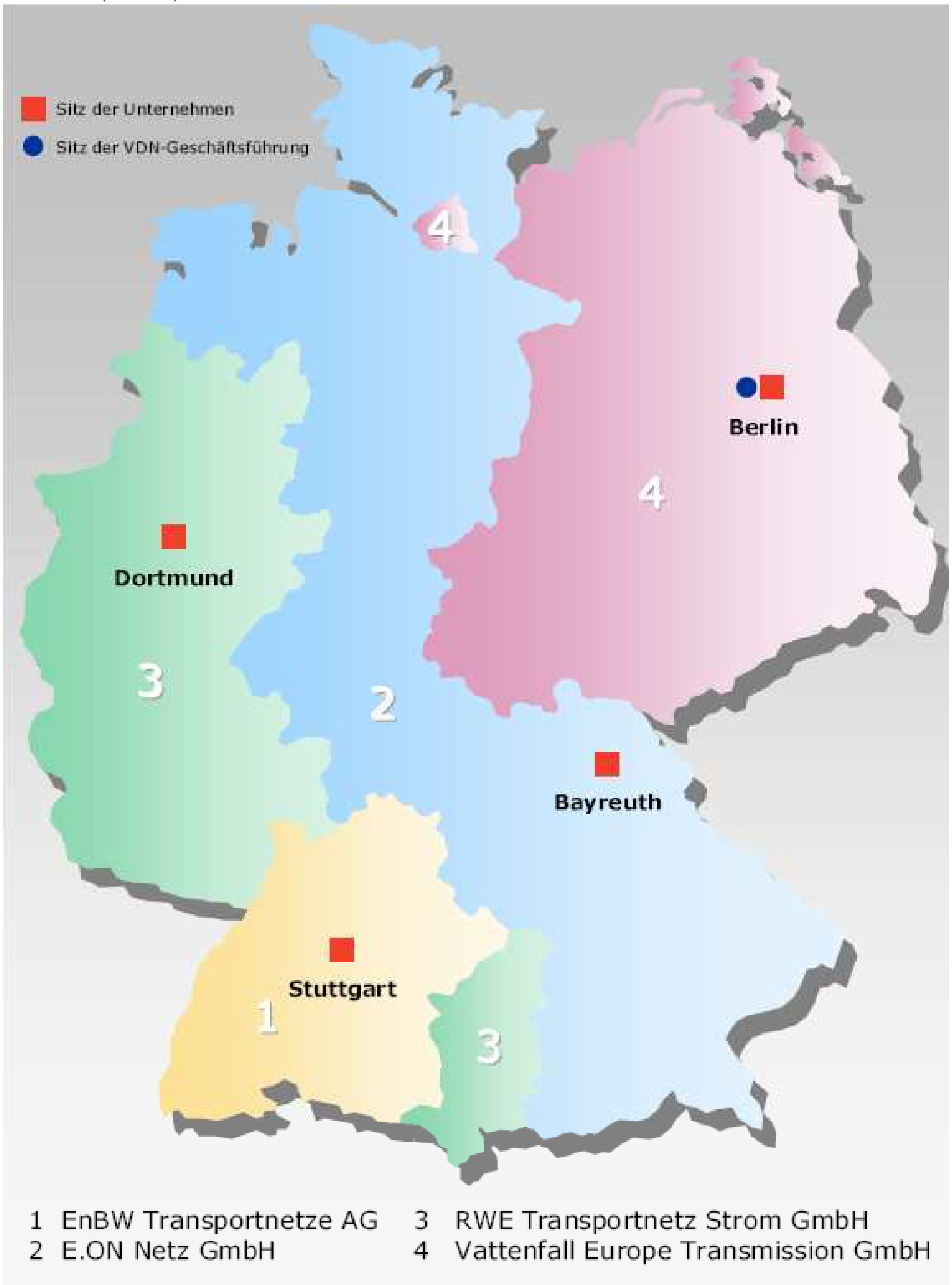
This is controversial because it encourages speculation about the net deviation. Such speculations support network stability by compensating deviations with a countering deviation when it is successful. However, it is potentially endangering network stability by amplifying deviations when it is false. Other European countries therefore employ a dual-price settlement scheme. In fact, the German scheme also acknowledges the potentially destabilizing effect of speculative positions and penalties are set in network-access contracts for an abuse, i.e., excessive speculation. Nevertheless, speculation is allowed within limits, and certainly encouraged by the high price spread between positive and negative net deviation periods. For a more detailed discussion of network access contracts refer to Appendix B.

Another peculiarity of the German balancing energy market design is the discrepancy between the balancing energy settlement periods of quarter-hours and the minimal tradable period in the day-ahead and intra-day market of one hour. Therefore, it is practically impossible for a BRP to reproduce its electricity portfolio with corresponding contracts on a sub-hourly time scale. This aspect is employed for the direct analysis of the interplay of balancing energy with the capacity reserve market because an influence of the day-ahead market can be neglected on this time scale.

2.3.3 Market concentration

After the liberalization of the German electricity market in 1998 four big vertically integrated players formed that dominate the German market on all levels. These four players are: E.ON AG (e.on), Rheinisch-Westfälisches

Figure 2.3: The four German control areas. Source: Verband der Netzbetreiber (VDN).



Elektrizitätswerk AG (RWE), EnBW Energie Baden-Württemberg (EnBW) and Vattenfall and their multiple specialized subsidiary companies.

This market concentration is most obvious in the transmission system, where the corresponding four subsidiary companies constitute the four German TSOs. (See Figure 2.3). It is argued this division of the German market was unnecessary and a combined German control area would be more efficient by netting the deviations of the current control areas. (See Bundes Netz Agentur(2009; 2010)). The issue of concentration in the transmission system was also raised by the European commission that continuously works towards an unbundling. In the last year the market moved into this direction. All but the RWE control area use a common balancing energy price based on the net-deviation of the corresponding three control areas. Also, the transmission system of e.on and Vattenfall were sold to a Dutch and Belgian competitor.

In terms of electricity generation the four biggest players account for almost 90% of generation. This high level of concentration is persistent over time when assessing certain market situations as was confirmed in EU (2007). However, it should be noted that the influence of interconnection lines has to be taken into account. This raises again the issue of vertically integrated companies and the transmission system operation by the four biggest players.

Undoubtedly the market shows to be concentrated, but this gives no indication of the potential abuse of market power. Several studies identify signs of such abuse in an analysis of prices at the EEX. However, these results are controversial as such studies necessarily rely on model assumptions and simplifications. (See Ockenfels (2007a; 2007b) and Möst and Genoese (2009)). As of now, no company was convicted of market power abuse, and the issue remains open. A more detailed discussion of the analysis of market power in the German electricity generation is added in Appendix A.

In the retail market the dominance of the four biggest players is less pronounced and they amount to a market fraction of about 50%. However, retail prices contain tax and network charges as a large fraction. This fixed price component of retail prices dampenes competion in the retail market, and the completion is strongest for large scale consumers where small price differences tip the balance.

The general picture of market concentration in the electricity market mirrors the situation in the neighboring countries. This underlines the importance of regulation and an efficient market design.

Chapter 3

Methods and mathematical concepts

In this chapter mathematical methods and concepts used throughout this work are introduced. It is focused on econometric time series analysis in discrete time, reflecting the data set of quarter-hourly balancing energy demand the analysis in this thesis is based on. (Refer to Appendix D for detailed information on the data). The essence of time series models is to capture aspects of phenomena that are constant over time and aspects that are random in one model. Such a model provides a reliable forecast of the phenomena while at the same time describing the risk associated with this forecast.

3.1 Linear time series models

In a econometric model in discrete time a time series is regarded as a realization of a sequence of a random variable x_t. In particular, a situation is considered where the only available information is the time series itself. Despite this limitation a forecast is feasible under certain conditions. This section is focused on linear time series models. In these models an additional factor the innovation time series (ϵ_t) is introduced. This factor represents the randomness in the model. One such example is the Gaussian white noise process where each time step is a realization of an independent drawing from a normal-distribution (a i.i.d. sequence of $\mathcal{N}(0, \sigma^2)$). In this simple example the forecast is zero and the risk is captured by the constant σ.

3.1.1 Preliminary conditions

Time series have to have certain properties to make forecasting by linear models feasible. The most important property is stationarity. For a forecast a time series has to have a property that stays constant over time, so that it can be continued into the future. A process is *strictly stationary* if the joint distribution of an arbitrary sequence is invariant with respect to an arbitrary shift in time. This condition is expressed in the following equation:

$$(X_t, X_{t+1}, \dots X_{t+n}) \stackrel{d}{=} (X_{t+h}, X_{t+1+h}, \dots X_{t+n+h}) \; \forall t, h$$

The independent identically distributed (i.i.d.) sequence is a strictly stationary process but allows for very little dynamic. Relaxing the conditions of stationarity leads to the concept of *weakly* or *covariance stationary* processes. Formally, a process is *weakly stationary* if it satisfies the following conditions:

$$\begin{aligned} E(x_t) &= \mu \; \forall t \\ Cov(x_t, x_{t-h}) &= \gamma_h \; \forall t, h \end{aligned}$$

A weakly stationary process has time independent first and second moments. However, the covariance may depend on the time lag. Moreover, any stationary process with finite first and second moment is weakly stationary. Without a loss of generality the mean can also be assumed to be zero because any stationary time series with non-zero mean can be transformed into a zero mean time series $(x_t - \mu)$. For convenience, the term stationary is used in the meaning of weak stationarity in the remainder of this thesis.

Two characteristics are important about stationarity. First, the time independent first and second moment form a basis to forecast the time series. In combination with the Gaussian white noise this allows for a quantification of the risk of these forecasts, as well. Second, any stationary time series can be expressed as a possibly infinite linear time series model. The feature is known as the Wold's decomposition theorem and guaranties the theoretical feasibility to tackle stationary time series with linear models.

3.1.2 Moving average models

Specifically, the Wold's decomposition theorem states the following for a stationary process $((x_t))$:

$$x_t = \epsilon_t + \sum_{i=1}^{\infty} \theta_i \epsilon_{t-i} \, , \text{where} \sum_{i=0}^{\infty} |\theta_i| < \infty \tag{3.1}$$

Any stationary time series can be expressed by a linear combination of some innovation process. Such a model is called a moving average (MA) process of order q, where q denotes the index of the last non-negligible summand.

Furthermore, the linear model relies exclusively on past innovations. This property is *causality* and can always be achieved by defining another time shifted innovation process. Despite the great flexibility of MA models spanning all stationary time series, the possibly infinite series of parameters θ_i can make the MA representation of a time series practically useless.

3.1.3 Autoregressive models

Another linear time series model is the autoregressive (AR) model of order p. In this model the time series is represented by a linear combination of its past p realizations, as follows:

$$x_t = \epsilon_t + \sum_{i=1}^{p} \phi_i x_{t-i}. \tag{3.2}$$

A MA(q) can also be represented by an AR(∞) model if the time series is so-called *invertible*. At the same time Wold's decomposition theorem still holds for a stationary time series. Therefore, a stationary AR(p) process can be represented as MA(∞). In fact, the AR and the MA representation are complementary in the sense that a stationary AR(1) model is represented by a MA(∞) model and an invertible MA(1) model is represented by an AR(∞) model. (See Appendix C.1.)

3.1.4 Autoregressive moving average models

As MA and AR model are complementary to each other, it is of much avail to combine the two. The combined model is the so-called autoregressive moving average (ARMA) model of order p, q with the orders of the AR and MA model, respectively. The key advantage of an ARMA representation lies in parameter parsimony. In the case of a stationary invertible time series both, a strict AR and MA representation, are theoretical feasible, however, the possibly infinite number of parameters make these representations impossible to estimate. Therefore, ARMA models are the most general representation for stationary invertible time series. After introducing the lag operator L ($L^i x_t = x_{t-i}$) the ARMA(p, q)-model in equation (3.3) can be expressed in terms of two polynomials in L in equation (3.4):

$$\begin{aligned} x_t &= \epsilon_t + \sum_{i=1}^{p} \phi_i x_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} && (3.3) \\ \phi(L)(x_t) &= \theta(L)\epsilon_t && (3.4) \end{aligned}$$

This representation can be a major convenience when working with an ARMA model, as the operator can be treated as a sort of multiplication. Applying this representation it is straightforward to show that the stationarity of a time series depends solely on the p parameters of the AR part of an ARMA process. (See Appendix C.2.)

3.1.5 Integrated autoregressive moving average models

All models presented above are limited to the precondition of a stationary time series. However, many time series do not fulfill this requirement. One such example is the random walk ($x_t = x_{t-1} + \epsilon_t$). To be able to model such a time series in the ARMA frame work it has to be modified. In the following, the time series transformed through the difference operator ($\Delta = 1 - L$) is considered. The new time series ($y_t = \Delta x_t = \epsilon_t$) is the stationary innovation time series introduced above. To obtain a model of the original time series the modeled innovations have to be added or integrated starting at some known point (x_0). Therefore, these models are called integrated autoregressive moving average (ARIMA(p, d, q))-models where the parameter d describes the order of differencing necessary to obtain a stationary time series. Equation (3.5) shows a general ARIMA(p, d, q) model:

$$\phi(L)\Delta^d(x_t) = \theta(L)\epsilon_t \tag{3.5}$$

It should be added that besides differencing the logarithm and the calculation of a return series are common techniques to transform a non-stationary time series into a stationary time series that can be described by an ARMA model.

3.1.6 Seasonal integrated autoregressive moving average models

The ARIMA model can capture seasonality, but in the event of two ARIMA processes governing the time series at different time scales, interdependence between these processes is introduced. (See Appendix C.3). This interdependence is captured by the seasonal integrated auto regressive moving average (SARIMA(p, d, q)$\times$(P, D, Q)$_s$) model as in equation (3.6):

$$\phi(L)\Phi(L^s)\Delta^d\Delta_s^D(x_t) = \theta(L)\Theta(L^s)\epsilon_t \tag{3.6}$$

Here the parameters p, d, q and P, D, Q are the parameters of the ARIMA processes at the basic interval and the seasonal interval (s), respectively.

3.1.7 Factor models

The discussion of linear models above is restricted to cases where there is no information outside the history of a time series. However, valuable information is often available in addition to the time series itself. The trajectory of such information is a random variable itself. In the style of factor analysis it is called a factor in this thesis. A time series can be regressed based on these factors (f) yielding a model of the type in equation (3.7):

$$x_t = \epsilon_t + \sum_{i=1}^{n} \beta f_{n,t}. \tag{3.7}$$

This form represents a very general class of models as it includes non-linear dependencies as well as an AR type regression on lagged values of a particular factor. Any concept of dependency that is more complex than the linear model can be fully ascribed to the definition of the factors. As an example one factor can be defined as the lagged value of a random variable or as any function thereof.

3.2 Innovation process

The discussion of the linear time series models above concentrates on the description of predictable components and attributes the randomness to the innovation process (ϵ_t). This section is focused on the description of the innovation process. In this context the linear time series model can be regarded as a filter extracting the innovation process from the time series.

In describing the randomness, the innovation process is crucial in capturing the risk involved in the forecast of a particular time series. Whenever the inevitable error of a forecast has to be countered by appropriate measures, one has to rely on the specification of the innovation process to appropriately dimension these measures in advance.

In general, there is an abundance of distributions that can be used to describe an innovation process. However, the innovations can often be considered to be caused by many independent events with their magnitude described by one common distribution. In this case, the general central limit theorem (gCLT) marks out the class of α-stable distributions for modeling the innovation process. As the sum of any appropriately scaled series of independent random variables will converge in distribution to a member of this class. In other words, whenever many individual shocks have to be considered at the same time α-stable distributions are the natural choice for modeling these innovations.

3.2.1 Normal distribution

The general central limit theorem is often better known on a specialized subset as the central limit theorem (CLT). It states that the sum of a series of independent random variables from a common distribution with finite first and second moment converges in distribution to a normal distribution. It can be defined by its probability density function that is given in equation (3.8):

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/2\sigma^2} \tag{3.8}$$

The two defining parameters are:

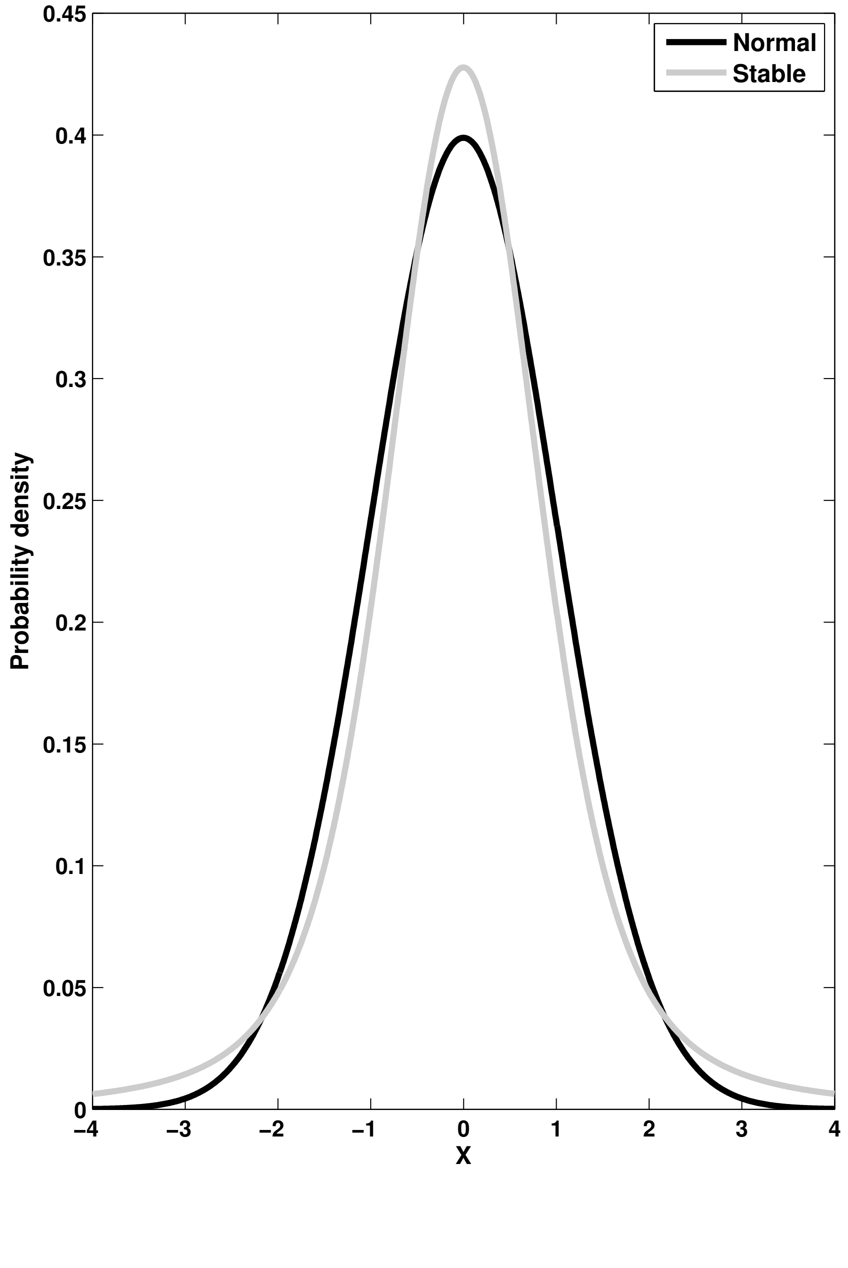
- σ: the scale parameter, $\sigma \in (0, +\infty)$;
- μ: the location parameter, $\mu \in (-\infty, +\infty)$.

Through centering and rescaling, the distribution can be confined to the standard normal distribution with parameters $\mu = 0$ and $\sigma = 1$ that is displayed in Figure 3.1. The existence of a simple closed-from expression for the density in combination with the central limit theorem might explain the normal distribution to be the standard assumption of classical time series analysis. However, often phenomena are exposed to extreme events that are extremely improbable under the assumption of a normal distribution. Two reasons might be the course of this discrepancy from the normal distribution. First, the condition of finite first and second moments of the underlying distribution might not be fulfilled. Second, the number of summands might be too small to allow a sufficient convergence towards the theoretical limiting distribution (i.e., the time scale under consideration is too short to apply the limiting distribution). In fact, the convergence to the normal distribution may be arbitrarily slow.

3.2.2 α-stable distribution

By relaxing the assumption of finite first and second moments of the underlying distribution, the central limit theorem is generalized. The general central limit theorem defines a set of distributions that the distribution of the sum of any identical independent distributed random variable will converge to. This set of distributions is the set of α-stable distributions. In general, there is no closed form expression for the density function of α-stable distributions. Therefore, α-stable distributions are characterized in

Figure 3.1: Probability density of the standard normal distribution and a standard α-stable distribution ($\alpha = 1.5$)



the frequency domain by their characteristic function as in equation (3.9):

$$\phi_{\text{stable}}(u;\alpha,\sigma,\beta,\mu) = E[e^{iuX}] \tag{3.9}$$
$$= \begin{cases} \exp\left(i\mu u - |\sigma u|^{\alpha}\left(1 - i\beta(\text{sign u})\tan\frac{\pi\alpha}{2}\right)\right), & \alpha \neq 1 \\ \exp\left(i\mu u - \sigma|u|\left(1 + i\beta\frac{2}{\pi}(\text{sign u})\ln|\text{u}|\right)\right), & \alpha = 1, \end{cases}$$

where

$$\text{sign t} = \begin{cases} 1, & t > 0 \\ 0, & t = 0 \\ -1, & t < 0 \end{cases}$$

In this parameterization, the four parameters $(\alpha, \beta, \sigma, \mu)$ have the following domain and interpretation:

- α: the index of stability or the shape parameter, $\alpha \in (0, 2)$;
- β: the skewness parameter,$\beta \in [-1, +1]$;
- σ: the scale parameter, $\sigma \in (0, +\infty)$;
- μ: the location parameter, $\mu \in (-\infty, +\infty)$.

Figure 3.1 shows an α-stable distribution together with a standard normal distribution. Two important effects can be observed that result in four intersections of the probability density functions. First, the α-stable distribution is more peaked around the center of the distribution. Second, the α-stable assigns more weight to the tail of the distribution. The normal distribution is a special case of an α-stable distribution where the parameter α is two and the parameter β has no effect. It links the general central limit theorem to the central limit theorem discussed in the previous section. Commonly, the parameters are estimated in the frequency domain as there are only two additional cases with a closed form density function besides the normal distribution.

The advantageous feature of α-stable innovations lie in constant parameter α when adding the effect of i.i.d distributed events over arbitrary time horizons. Specifically, this allows the adequate description of risk. However, a non-existent second moment and, in the case of α less or equal to one, a non-existent first moment, are often too strong an assumption and pose a considerable drawback in many applications.

3.2.3 Tempered stable distribution

In many applications it is possible to constrain the domain of the underlying distribution. Mathematically speaking, this results in all moments to be finite. Therefore, such phenomena are clearly in the domain of the central limit theorem with the normal distribution as the limiting distribution for the infinite sum of independent random drawings from the underlying distribution. However, the convergence to the normal distribution can be slow.

For such intermediate cases that are in the theoretical limiting domain of the normal distribution but show excess kurtosis and possibly skewness, the class of tempered stable distributions has been proposed. (See Menn *et al.* (2005), Kim *et al.* (2008), and Menn and Rachev (2009).) This class is designed to resemble an α-stable distribution at the center of the distribution. However, in contrast to the general α-stable distribution the tails decay-off exponentially. Like the α-stable distribution the tempered stable distribution is characterized in the frequency domain by its characteristic function as in equation (3.10):

$$\begin{aligned}\phi_{CTS}(u; \quad & \alpha, C, \lambda_+, \lambda_-, m) = \exp(ium - iuC\Gamma(1-\alpha)(\lambda_+^{\alpha-1} - \lambda_-^{\alpha-1}) \\ + \quad & C\Gamma(-\alpha)((\lambda_+ - iu)^\alpha - \lambda_+^\alpha + (\lambda_- + iu)^\alpha - \lambda_-^\alpha)). \qquad (3.10)\end{aligned}$$

Here m and C determine the location and scale as do μ and σ in the α-stable distribution. The parameters λ_+ and λ_- allow for skewness as well as a faster than α-stable decay in the tails. Figure 3.2 and 3.3 compare the probability density function of a CTS and an α-stable distribution. The additional parameter allows for a more peaked probability density near the center of the distribution. As in the case of the standard normal and an α-stable distribution this causes four intersections of the respective density functions (i.e., the CTS distribution has a more heavy-tailed appearance near the center). At the same time the probability density's exponential decay in the fare-tail assigns less weight to these extreme events. This causes another two intersections of the probability density functions.

In this work the name classical tempered stable (CTS) distribution is used. It should be noted, however, the tempered stable distribution has been introduced under different names in the literature including the truncated Levy flight by Koponen (1995), the KoBoL distribution by Boyarchenko and Levendorskiĭ (2000), and the CGMY distribution by Carr *et al.* (2002). The fundamental feature is the combination of fast decaying extreme tails with a highly peaked center of the distribution. The first feature guaranties finite moments while the second feature allows to access the broad range of relations of the small to the extreme events given by α-stable distributions.

Figure 3.2: Probability density of a standard CTS and a standard α-stable distribution, parameters as in Table4.7

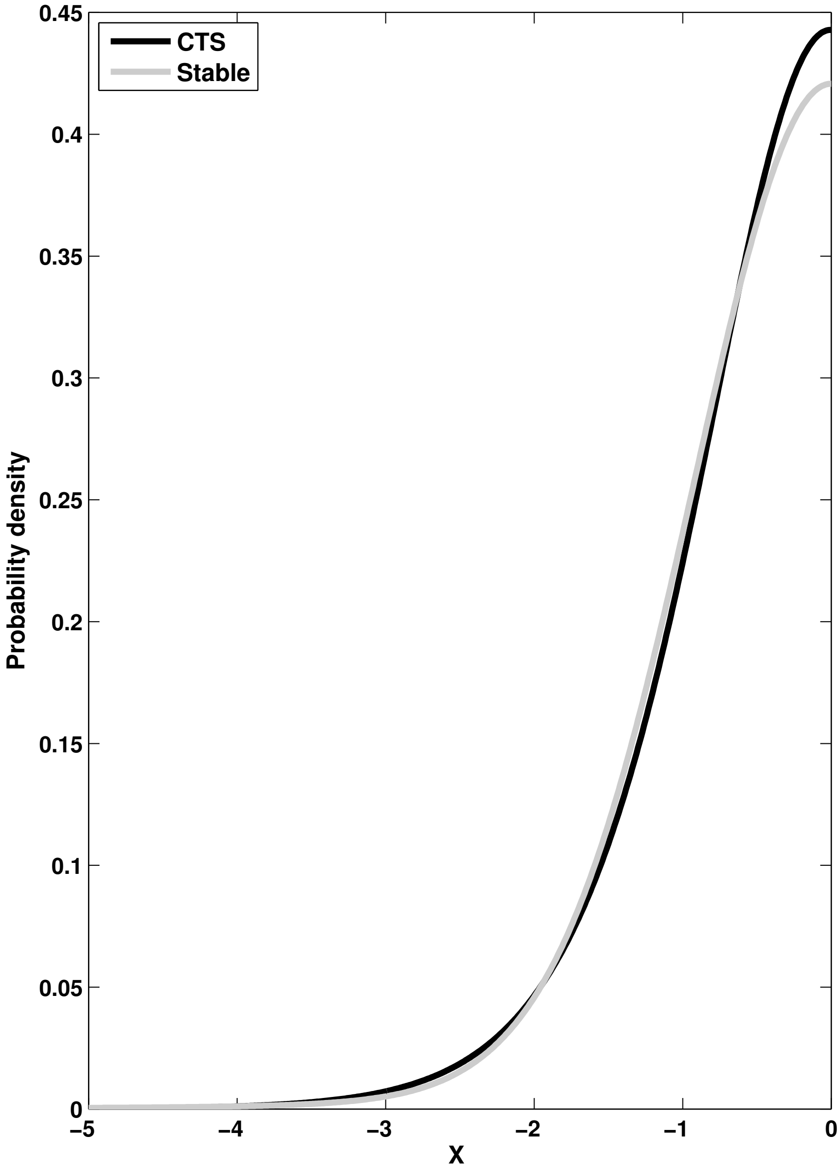
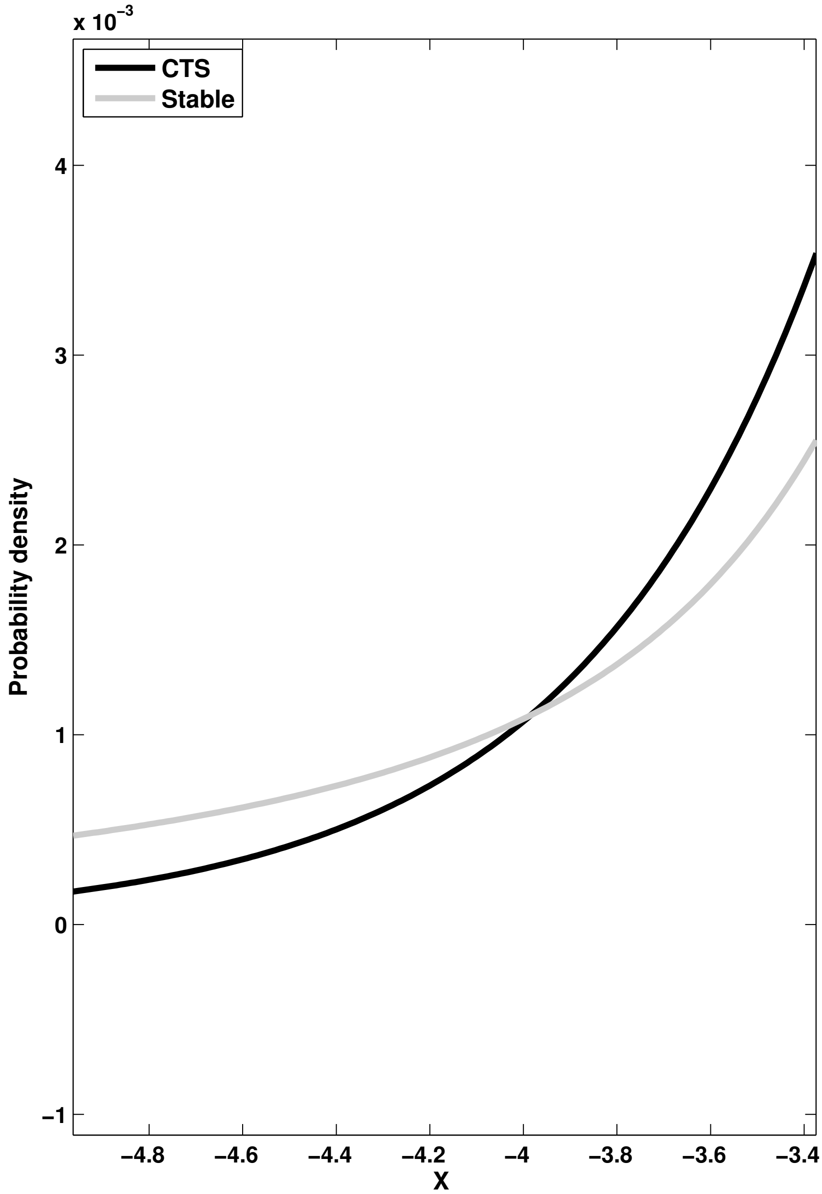


Figure 3.3: Tail of probability density of a standard CTS and a standard α-stable distribution, parameters as in Table4.7



3.2.4 Goodness-of-fit tests

Both the α-stable distribution and the tempered stable distribution introduce additional parameters in the model as compared to the normal distribution. To conclude the discussion of the innovations process, methods to guide in the selection of the appropriate innovations distribution are discussed. Among these methods are visual methods to display the available information to get an insight about the appropriate distribution, and statistical tests that are able to quantify the distribution selection problem.

Quantile-quantile plot

The quantile-quantile (QQ) plot is a widely used graphical inspection method. It displays the theoretical quantiles of the proposed distribution plotted versus the empirical quantiles of the observed innovations as filtered from the time series. If the data corresponds well to the proposed distribution, the QQ-plot will mark a straight line of slope one. A QQ-plot that marks a shifted straight line or a line of different slope indicates an inadequate specification for the parameters of location and scale of the theoretical distribution. More importantly in the context of innovations is a non-linear QQ-plot. Figure 3.4 shows the QQ-plot of heavy-tailed data and the assumption of the normal distribution. Here, the flattening of the QQ-plot indicates the higher probability of extreme events in the empirical data.

The QQ-plot is a visual inspection technique and is therefore subjective. The advantage of the QQ-plot is that it allows a conclusion about the fitness of the proposed distribution for the innovations. Additionally, it provides information about the type of difference between the empirical distribution and the suggested distribution.

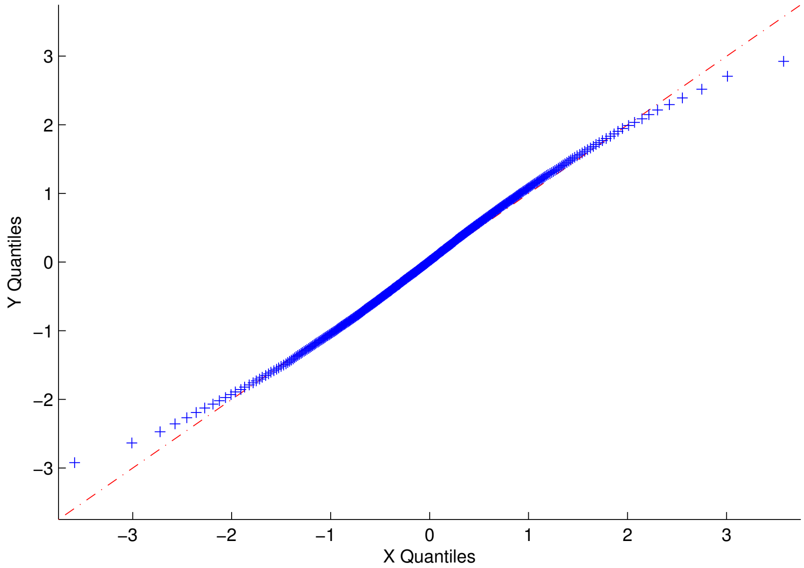
Kolmogorov-Smirnov test

For an objective classification of the distribution's fitness goodness-of-fit tests are developed. The Kolmogorov-Smirnov (KS) test is set up to test the null-hypothesis of the empirical distribution to follow the suggested distribution. Its test statistic is based on the maximal distance of the empirical cumulative density function ($F_{emp.}(x)$) and the empirical and theoretical cumulative density function ($F_{theo.}(x)$):

$$KS = \sqrt{n} \sup |F_{emp.}(x) - F_{theo.}(x)|$$

The KS test statistic can than be compared to critical values that are listed corresponding literature and implemented in standard statistical software

Figure 3.4: QQ-plot of heavy-tailed data (X) under the Gaussian hypothesis (Y)



packages.

Anderson-Darling test

The KS statistic measures the vertical distance of the empirical and theoretical cumulative density function. Therefore, it is most sensitive to deviations close to the center of the distribution where the cumulative density function runs almost vertically. However, the risk of extreme events in the tails is often in the focus of a particular analysis. To assign more weight to the tails of the distribution the distance of the empirical cumulative density function ($F_{emp.}(x)$) and the empirical and theoretical cumulative density function ($F_{theo.}(x)$) is scaled in the Anderson-Darling (AD) test statistic:

$$AD = \sqrt{n} \sup \left| \frac{F_{emp.}(x) - F_{theo.}(x)}{\sqrt{F_{theo.}(x)(1 - F_{theo.}(x))}} \right|$$

The scale factor $(1/\sqrt{F_{theo.}(x)(1 - F_{theo.}(x))})$ reaches its minimum at the center of the distribution thereby enhancing the importance in the tails.

Cramer-von Mises test

Both the KS-test and the AD-test rely on a single value from the sample, the maximal distance that is weighted in the latter case. The Cramer-von Mises (CvM) test is designed to account the differences of the empirical and the theoretical cumulative density function over the total sample size:

$$CvM = n \int_{-\infty}^{\infty} (F_{emp.}(x) - F_{theo.}(x))^2 dF_{theo.}(x)$$

As the definition shows the CvM-test statistic depends on the area between the empirical and theoretical cumulative density function. In contrast to the KS-test the critical values of the CvM-test depend on the distribution analyzed. However, they can be estimated in a Monte Carlo simulation.

Squared Anderson-Darling test

As in the case of the KS-test the CvM-test can be modified to assign more weight to the tails of the distribution. This modified test is called quadratic Anderson-Darling (AD^2) test:

$$AD^2 = n \int_{-\infty}^{\infty} \frac{(F_{emp.}(x) - F_{theo.}(x))^2}{F_{theo.}(x)(1 - F_{theo.}(x))} dF_{theo.}(x)$$

As in the case of the CvM-test the critical values have to be estimated in a Monte Carlo simulation.

3.3 Model building

The linear model and the innovation process are the fundamental building blocks to model a given time series. In this section the approach to model-selection proposed by Box and Jenkins (1970) is described.

3.3.1 Unit root

Stationarity is a necessary condition for the linear time series models presented in Section 3.1. In the case of an integrated process stationarity is achieved by an appropriate transformation of the time series. Therefore, the time series has to be tested for the presence of a unit root. The time series can be modeled in the described framework only if it is stationary and the presence of a unit root can be rejected.

A standard test for a unit root is the *augmented Dickey-Fuller* test. (See Dickey and Fuller (1979).) The null hypothesis of a unit root is tested by estimating an AR model of order p for the once differenced time series also including the un-differenced realizations of lag one. Equation (3.11) shows the underlying regression model:

$$\Delta x_t = \epsilon_t + \gamma x_{t-1} + \phi_p(L)\Delta x_{t-1} \tag{3.11}$$

Under a true null hypothesis the parameter γ has to be compatible with zero. However, if the parameter γ significantly deviates from zero the differenced time series can be regarded as over-differenced or, equivalently, the time series shows no indication of a unit root. The parameter p has to be selected high enough to capture the relevant structure of the time series. Generally, the test less likely rejects the null hypothesis the higher the value p is.

Should a unit root not be rejected the test has to be repeated for the differenced time series until a unit root can be rejected. In this way multiple roots are accounted for and the appropriate degree of differencing for a given time series can be determined.

3.3.2 Sample autocorrelation function and sample partial autocorrelation function

In this section a stationary invertible time series that can be represented by an ARMA(p, q) process centered around zero is considered. The two orders p and q are unknown and have to be identified. This identification can be based on the autocorrelation function (ACF) and the partial autocorrelation function (PACF) or more precisely their respective sample estimations (SACF and SPACF). As discussed in Section 3.1, the time series can be represented as both a MA and an AR process. It can be shown that the ACF of a finite MA(q) process will vanish at the q-th lag while the PACF of a finite AR(p) process vanishes after the p-th lag. Therefore, the sample estimates of the ACF and the PACF give an indication of the appropriate orders for the estimation of a general ARMA(p, q) process. The selected models can than be estimated and compared.

Autocorrelation function

The discussed ARMA model relies on information from past observations of the time series. To capture this, the autocorrelation (ρ) of the time series can be calculated at different lags (k):

$$\rho_k = Cov(x_t, x_{t-k})/Var(x_t)$$

Looking closer at the covariance and using the representation of the ARMA process by polynomials given in equation (3.3) the following results:

$$\begin{aligned}
\gamma_k &= Cov(x_t, x_{t-k}) = E(x_t \cdot x_{t-k}) = E(x_{t-k} \cdot x_t) = \gamma_{-k} \\
&= E((\epsilon_t + \sum_{i=1}^{p} \phi_i x_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i}) \cdot x_{t-k}) \\
&= \phi_1 \gamma_{k-1} + \dots \phi_p \gamma_{k-p} \\
&+ E(\epsilon_t \cdot x_{t-k}) + \theta_1 E(\epsilon_{t-1} \cdot x_{t-k}) + \dots \theta_q E(\epsilon_{t-q} \cdot x_{t-k})
\end{aligned}$$

Using the invertibility of the time series x_{t-k} it can be expressed by a MA process:

$$\begin{aligned}
& x_{t-k} = \frac{\theta(L)}{\phi(L)} \epsilon_{t-k} \equiv \tilde{\theta}(L)\epsilon_{t-k} = \sum_{i=0}^{\infty} \tilde{\theta}_i \epsilon_{t-(k+i)} \\
\Rightarrow \quad & E(\epsilon_{t-l} x_{t-k}) = E(\epsilon_{t-l} \sum_{i=0}^{\infty} \tilde{\theta}_i \epsilon_{t-(k+i)}) = \begin{cases} \tilde{\theta}_{l-k}\sigma^2, & \forall \quad l \geq k \\ 0, & \forall \quad l < k \end{cases} \\
\Rightarrow \quad & \gamma_k = \sum_{i=1}^{p} \phi_i \gamma_{k-i} + \sigma^2 \cdot \mathbb{1}_{[1,q]}(k) \sum_{j=k}^{q} \theta_j \tilde{\theta}_{j-k} \\
\Rightarrow \quad & \rho_k = \underbrace{\sum_{i=1}^{p} \phi_i \rho_{k-i}}_{AR(p)} + \underbrace{\mathbb{1}_{[1,q]}(k) \sum_{j=k}^{q} \theta_j \tilde{\theta}_{j-k}}_{\mathrm{MA}(q)} \qquad (3.12)
\end{aligned}$$

Equation (3.12) has two summands for the AR and the MA part of the process, respectively. The summand of the AR part shows the same autoregressive behavior as the time series and, therefore, slowly decays to zero with increasing k. In contrast, the summand of the MA part abruptly falls to zero as k increases to values lager than q in the indicator function.

On a finite sample of a time series of size N the autocorrelation function has to be estimated. Equation (3.13) shows the computation formula suggested in Rachev *et al.* (2007):

$$\hat{\rho}_k = \frac{\sum_{i=k+1}^{N} (x_i - \bar{x})(x_{i-k} - \bar{x})}{\sum_{i=1}^{N} (x_i - \bar{x})^2} \qquad (3.13)$$

Implicitly, the estimators of the covariance in the numerator and the variance in the denominator are normalized by the same factor in this computation. This disregards that the covariance has k summands less than the variance. However, this bias is insignificant for lags k that are much smaller than the sample size N. At the same time it guaranties the estimated autocorrelation function of the given time series to be associated with a stationary time series thereby increasing the robustness of the calculation (Rachev *et al.* (2007)).

Partial autocorrelation function

The autocorrelation function represents the unconditional correlation of two realizations separated by lag k. In contrast, the partial autocorrelation (α) represents the correlation between to realizations separated by lag k conditional on the correlation that might exist to intermediate realizations. In other words, the partial autocorrelation is the k-th coefficient of an autoregression model where the contribution of the intermediate lags is taken as given:

$$\alpha_k = \frac{Cov(x_t, x_{t-k}|x_{t-1}, \ldots x_{t-(k-1)})}{Var(x_t)}.$$

To obtain the partial autocorrelation function a pure AR estimation of order k^* is applied for each lag. Taking the expectation value results in the set of equations of the autocorrelation function of the pure AR(k^*) process for each lag given in equation (3.12):

$$\begin{aligned} \rho_k &= \sum_{i=1}^{k^*} \tilde{\phi}_i \rho_{k-i} \\ \Rightarrow \alpha_{k^*} &= \tilde{\phi}_{k^*} \end{aligned}$$

This set of equations is called *Yule-Walker* equations. Based on the known autocorrelation ρ_k the coefficients $\tilde{\phi}_i$ can be calculated. Considering a time series that is described by an AR(p) process, the coefficients of an applied process $\tilde{\phi}_i$ are zero for all lags greater than p as the time series is fully described by the first p coefficients. In contrast, a pure MA process has an AR representation of infinite order. Therefore, its partial autocorrelation function will only decay to zero.

The estimate of the PACF can be calculated by using the estimates of the autocorrelation and successively solve the Yule-Walker equations for each lag. It is useful to base this estimation on a matrix representation of the Yule-Walker equations:

$$\begin{bmatrix} 1 & \hat{\rho}_1 & \dots & \hat{\rho}_{k^*-1} \\ \hat{\rho}_1 & 1 & & \hat{\rho}_{k^*-2} \\ \vdots & & \ddots & \vdots \\ \hat{\rho}_{k^*-1} & \hat{\rho}_{k^*-2} & \dots & 1 \end{bmatrix} \begin{bmatrix} \tilde{\phi}_{k^*,1} \\ \vdots \\ \tilde{\phi}_{k^*,k^*-1} \\ \tilde{\phi}_{k^*,k^*} \end{bmatrix} = \begin{bmatrix} \hat{\rho}_{k^*,1} \\ \vdots \\ \hat{\rho}_{k^*,k^*-1} \\ \hat{\rho}_{k^*,k^*} \end{bmatrix}$$

$$\mathbf{Y}_{k^*}\tilde{\phi}_{k^*} = \hat{\rho}_{k^*}$$

In this representation the value of the PACF can than be found by applying Cramer's rule resulting in equation (3.14):

$$\hat{\alpha}_{k^*} = \frac{det(\mathbf{Y}_{k^*,k^*})}{det(\mathbf{Y}_{k^*})} \tag{3.14}$$

In fact this procedure can be used to estimate the parameters of a purely autoregressive model of order p where the sample partial autocorrelation function is an estimate of the model parameters.

3.3.3 Estimation

Based on the inspection of the sample autocorrelation function and the sample autocorrelation function, appropriate orders for an ARMA(p, q) representation of a time series are selected for further inspection. The parameters of these selected ARMA(p, q) representations have to be estimated to compare the representations. As stated in the previous section the parameters of a purely autoregressive model can be estimated using the sample partial autocorrelation function. However, in the case of a general ARMA(p, q) model the estimation is complicated by the unknown innovations time series.

A popular concept to estimate the parameters is the maximum likelihood (ML) procedure. This procedure searches the parameter space to identify the parameter set that makes the realized time series most probable. In statistical terms the ML procedure maximizes the joint probability density of all realizations. It is convenient to start the estimation at the $p + 1$-th observation to avoid the problem of estimating the initial values. Also, the first innovations are estimated by their expectation value (i.e., zero). Under these assumptions the joint probability density function can be decomposed into a series of independent density functions, namely the innovations. In turn the distribution type of the innovations can be set, for example to the normal distribution:

$$\begin{aligned} & f(x_T, \ldots x_{p+1}|x_p, \ldots x_1, \epsilon_p = 0, \ldots \epsilon_{p-q+1} = 0; \phi, \theta, \sigma^2) \\ = & \prod_{i=p+1}^{T} f(x_i|x_i - 1, \ldots x_1, \epsilon_p = 0, \ldots \epsilon_{p-q+1} = 0; \phi, \theta, \sigma^2) \\ = & \prod_{i=p+1}^{T} \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{(\epsilon_i)^2}{2\sigma^2}} \\ where \quad & \epsilon_i = x_i - \sum_{j=1}^{p} \phi_j x_{i-j} + \sum_{j=1}^{q} \theta_j \epsilon_{i-j} \end{aligned}$$

In other words, the density function conditional on the past observations is the density function of the innovations centered on the linear forecast based on the past observations. Transforming the likelihood function by taking the logarithm results in the log-likelihood function in equation (3.15):

$$\begin{aligned} & \ln L(x_T \ldots x_{p+1}; \phi, \theta, \sigma) \\ = \quad & -0.5T \cdot ln(2\pi) - 0.5T \cdot ln(\sigma^2) - 0.5\sigma^{-2} \sum_{i=p+1}^{T} \epsilon_i^2. \end{aligned} \tag{3.15}$$

Once the log-likelihood function is established it can be used in an iterative maximization procedure. As the number of parameters might be high it is important to employ a suitable search algorithm such as the gradient decent or Newton's method.

3.3.4 Diagnostic checking

In general, the model selection has to balance the description of the realized time series with the complexity of the model. A higher number of parameters allows the model to capture the behavior of the realized time series better but it introduces the risk of capturing purely stochastic features and inevitably introduces an additional error from the parameter estimation.

As a first step the residuals of the estimated model can be inspected within the same frame work as the original time series. In particular, the residuals should present a sample ACF and a sample PACF that are compatible with a pure white-noise process. This notion is formalized in the Portmanteu tests like the Ljung-Box test. Its test statistic (Q) is based on the first K sample autocorrelations (ρ) of a sample of size (T) and is χ^2

distributed:

$$Q = T(T+2)\sum_{k=1}^{K}\frac{\hat{\rho}_k}{T-k}$$

It is important to note that the Ljung-Box test does not incorporate the number of parameters (n) and therefore favors highly parameterized models. Also, the test can only be used to reject a model based on its autocorrelated residuals but does not guarantee the independence of the residuals.

Two selection criteria are established to select among models that capture the relevant time series features. These criteria are the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). Both criteria can be calculated from the log-likelihood value in equation (3.15) of an estimated model, where a specific penalty term for the number of parameters (n) is added:

$$\begin{aligned} AIC &= -2\ln L + 2n \\ BIC &= -2\ln L + n \cdot \ln(T) \end{aligned}$$

Both criteria suggest selecting the model with the lowest value. As is evident from the definition, the BIC has a stronger focus on a low number of parameters than the AIC. No model can be rejected based on the AIC or BIC values. In addition, model selection should therefore always be guided by a careful inspection of the residuals.

Part II

Analysis of balancing energy strategies

Chapter 4

Patterns in the balancing energy demand

Following the discussion in Chapter 2 balancing energy can be regarded as a forecasting error because it accounts for the fluctuations and unpredictable events that are not included in the BRPs preliminary scheduled electricity feed-ins and withdrawals. From this point of view balancing energy demand should be unpredictable on any relevant time scale. That is a time scale that allows BRPs to adjust their portfolios. In the case of the German market this time scale is at most the billing period of one month in which the BRPs are informed about their deviations and the control area's net deviation.

At the same time balancing energy is physical transaction of energy and can therefore be used by BRPs to balance their forecasted feed-ins and withdrawals to some extent. Such positions in the balancing energy market shift the inevitable fluctuations towards the positive or negative, and allow an optimization of the preliminary schedule. However, just like the fluctuations intent positions in the balancing energy market have to be limited to ensure secure network operation.

The market designs introduced in Section 2.1 reflect a different weighting of these two aspects of the balancing energy market. In the case of the German market there are no strict boundaries for active positions, but rather fuzzy limits that are imposed by a system of balancing energy prices and penalties. (See Bundes Netz Agentur (2006)). In this chapter[1] the German balancing energy demand is analyzed for predictable components that contradict the interpretation of balancing energy as a pure forecasting error. In addition, a econometric model for these predictable components is build, which allows to quantify the fuzzy limits in empirical terms. This analysis is organized in three sections reflecting the different time scales and incentive

[1]This chapter is based on Möller *et al.* (2010) and Möller *et al.* (2009b)

structures that are associated with particular intent positions, and is based on the time span 2003-2008.

4.1 Literature review

Depending on the market design the incentives for an active position in the balancing energy market can be diverse. Longstaff and Wang (2004) analyze the price convergence of the day-ahead and the real-time market in the setting of the Pennsylvania — New Jersey — Maryland (PJM) electricity market. They find a sustained premium of the day-ahead forward contracts over the real-time market that they attribute to risk factors in the style of Bessembinder and Lemmon (2002). Moreover, Saravia (2003) observe in a similar study of the elecricity market in New York a reduction in the forward premium after the authorization of virtual bids in the real-time market (i.e., an enhancement of active positions by allowing purely speculative positions that are not motivated by the management of physical electricity transactions.) This example demonstrates how strategic positions in the balancing energy market contribute to an efficient functioning of an electricity market.

In contrast, other markets are designed to undermine any strategic position. One such example is the electricity market in the Netherlands. In the Netherlands the TSO follows the explicit objective to drive all BRPs to present preliminary schedules without active position in the balancing energy market. (See Beune and Nobel (2001)). Boogert and Dupont (2005) test the effectiveness of the market design in accomplishing this objective. They find that the dual-price market design does not allow profitable strategic positions even with the superior knowledge of the control area's future average net deviation. Only under the ex-ante knowledge of extreme fluctuations can a profitable strategy be implemented. Boogert and Dupont therefore conclude the strategic positions in the balancing energy market can be disregarded in the case of the Netherlands.

In general, a dual-price settlement scheme compromises the interaction of the balancing energy market with alternative marketplaces. Regardless, the marketplaces are interchangeable. Therefore, the specific pricing of balancing energy may lead to biased preliminary schedules nonetheles as the following two examples demonstrate. Kirschen and Garcia (2004) state that balancing energy is too expensive in the market in England and Wales. As a result, market participants keep their own reserve capacity rather than resorting to system reserves. Consequently, deviations will be actively managed even if an offsetting deviation exists somewhere else in the control area. This results in an inefficiently high allocation of reserve capacity because market participants refrain from selling reserve capacity to the TSO and buying back with the additional transaction cost (i.e., the market is in oversupply of production capacity). In contrast, Mielczarski *et al.* (2005) have argued that in Poland balancing energy is too inexpensive. So market participants use the system's reserve to supply about 4% of total electricity demand (i.e., the market is in undersupply). Also, Belmans *et al.* (2009) describe that the preliminary schedule can be distorted by the dual-price settlement scheme. Moreover, they identify this settlement scheme as a market entrance barrier because transaction costs are avoided by netting out fluctuations in a BRPs portfolio. Naturally, this is most effective in the portfolio of large players.

The single-price settlement scheme of the German market bridges the gap between the dual-price settlement scheme and the real-time market. It allows and encourages strategic positions in the balancing energy market, however, once initiated these positions cannot be adapted during the real-time operation. Nailis and Ritzau (2006) analyze the balancing energy prices in the four German control areas. However, they are unable to identify strategic positions and an interplay with the day-ahead market due to the high variability of the balancing energy prices. In the following analysis of the balancing energy demand this barrier is avoided and strategic positions are identified.

4.2 General model

It is helpful to discern five factors that influence balancing energy demand (D_B) on different time scales. Most prominent there is a non-predictable event risk (σ). This factor will be present in any balancing energy market because it is designed to settle electricity transactions caused by unpredictable events. In addition, the German balancing demand shows four other factors that correspond to the representation of the preliminary schedule. These factors are the gradient of load (∇L), a day-ahead market statistical-arbitrage incentive (I), a technical incentive (I_{tec}), and a varying general market position (f). Assuming independence of the four factors, these factors can be modeled separately, yielding equation (4.1) as a general model for balancing energy demand in this thesis:

$$D_B(t) = q(\nabla L(t)) + h(I(t), I_{tec}(t)) + f(t) + \sigma(t) \tag{4.1}$$

There is a twofold separation in the model. First, the model separates strategic positions according to the time scale to which they are applied. These time scales are the quarter-hour interval, the hour interval, and positions taken over extended periods of time. The presentation of the results is organized along the line of this separation. Second, the model separates positions corresponding to the two alternative marketplaces, the day-ahead market and the capacity reserve market. In particular, the balancing energy market is an alternative marketplace for the capacity reserve market on the quarter-hourly time frame, whereas the day-ahead market is regarded as the representative market on hourly and longer time frames (i.e., an equilibrium of day-ahead and capacity reserve market is assumed on these time frames.) All the model components —except for the σ term— demonstrate that market participants are not using their best minimum-variance forecast because they represent predictable components.

4.3 Quarter-hourly pattern

Balancing energy is set with quarter-hour settlement periods in Germany, whereas the smallest contractual period on the day-ahead market is one hour. This discrepancy creates a distinct pattern, which is appropriately termed the quarter-hourly pattern in this work. At the same time the longer contractual period in the day-ahead market inhibits any direct interaction with the balancing energy market on the sub-hourly time frame because no countering positions can be initiated. In fact, the balancing energy market constitutes the only liquid marketplace for electricity transactions on a sub-hourly time frame in Germany. (See Section 2.3)

4.3.1 Modeling approach

The model is based on a consideration of the situation during an hour with an increasing load. The minimum-variance forecast for this hour that is tradable in the day-ahead market is the mean load during that hour. With this forecast the deviation will be negative in the first and second quarter of that hour and positive during the third and fourth quarter of that hour. Obviously, the same argument with opposite signs holds for a load decline. This effect will be more pronounced the higher the gradient of the load during that hour is. This gradient effect is also observed by Nailis and Ritzau (2006). Consequently, the effect can be modeled by the average load during the four quarter-hour periods ($\bar{L}_q(t)$) and the average load during the corresponding hour ($\bar{L}_h(t)$). This leads to the model in equation (4.2):

$$q(\nabla L(t)) = q \cdot (\bar{L}_q(t) - \bar{L}_h(t)) \; q \in [0, 1) \tag{4.2}$$

Here, the parameter q represents the electricity producers' ability to keep to their step function profile of hourly scheduled production. Should consumption and production change at the same rate, the factor will be zero. A value of one indicates a perfect step function of output corresponding to a theoretical infinite ramping speed of power stations. Negative values are excluded for the parameter q because consumption is assumed not to follow the step function schedule of day-ahead contracts.

To test this model it is compared to the empirical average pattern retrieved from the balancing energy data. This average pattern is defined by the mean-balancing energy demand relative to the corresponding hour's mean value, conditional on the quarter-hour interval of a day. Figure 4.1 shows the resulting pattern using 2004 data. Here, the four quarter-hour intervals of each hour are joined by lines to sort the 96 values. Note that by definition this pattern cannot be influenced by effects on hourly or even longer time scale, as each hour segment is centered on zero. In particular, any influence of the day-ahead market is separated. These are discussed in Section 4.4 and Section 4.5.

An estimation of the parameter q using a 2004 load measurement in quarter-hourly resolution yields $q = 0.424$. Comparing the pattern retrieved from this model to the empirical pattern results in an R^2 equal to 0.8696, which is significant at the 0.1% significance level. This demonstrates the high explanatory power of the model for the quarter-hourly pattern. Additionally, fully exploiting the model's prediction could reduce the sample variance by 12.03%.

To improve the illustration, the depicted segments in Figure 4.1 are joined in Figure 4.2. In this figure the missing information on the gradient between two consecutive hours is estimated as the average of the adjacent segments. Figure 4.2 shows the joint pattern based on the load data scaled by an estimated parameter. Clearly, the empirical pattern resembles the average German load profile. This is yet another indication of the model's fitness. A close inspection shows a pronounced difference of model and data between interval 20 and 24. While the model predicts a gradual increase, the real data presents a plateau. This coincides with mid-load units synchronizing to the grid frequency and going online between five and six in the morning to cover the steep load increase of the following hours. Consequently, the ability of the production side to follow the step function of day-ahead contracts is reduced in that hour. In the context of the hourly pattern this results in an even more pronounced effect that will be discussed in Section 4.4. In general, the model in equation (4.2) cannot capture such technical aspects in the quarter-hourly pattern. However, such aspects can be regarded as constant over the analyzed period.

To further investigate the quarter-hourly pattern, the patterns of all years in the interval 2003 to 2008 are therefore retrieved. These patterns

Figure 4.1: Expected quarter-hourly deviation conditional on the interval during a day (quarter-hourly pattern). Intervals forming an hour are joined by lines.

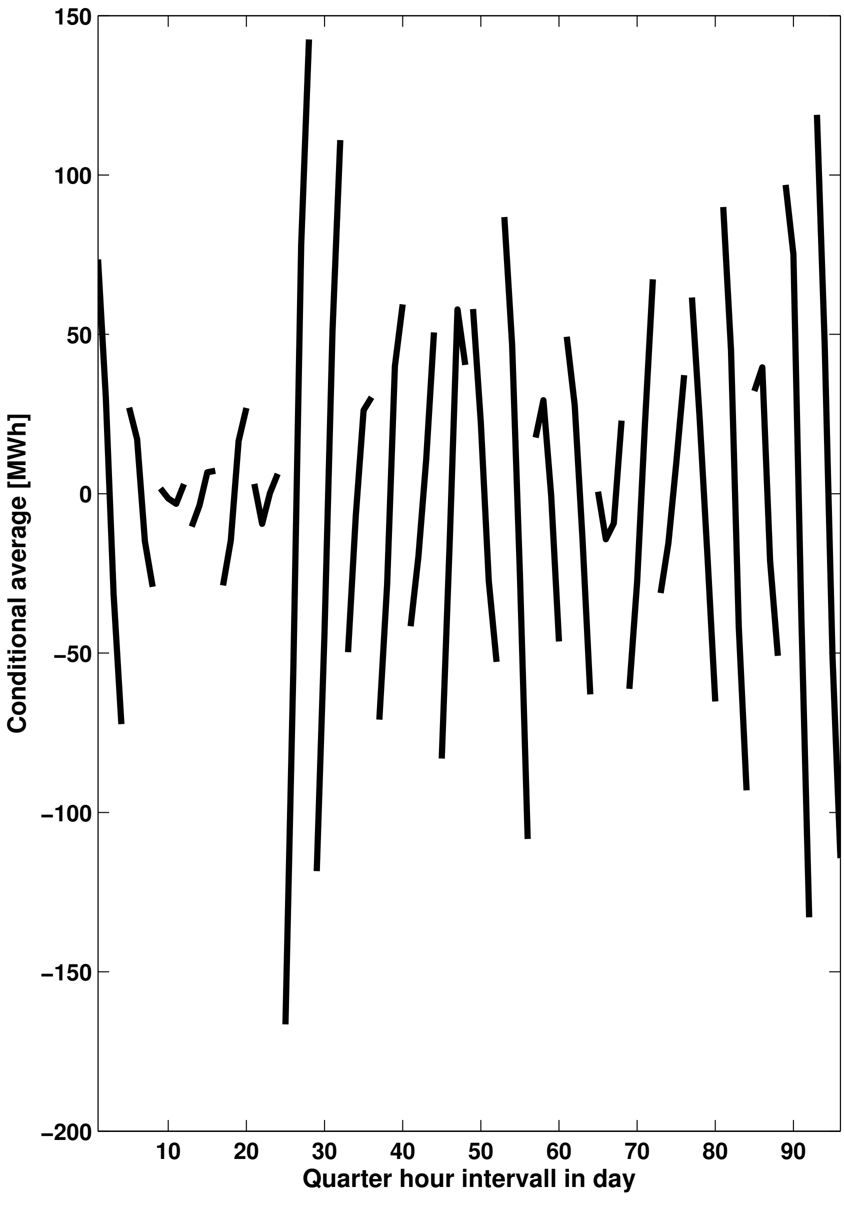
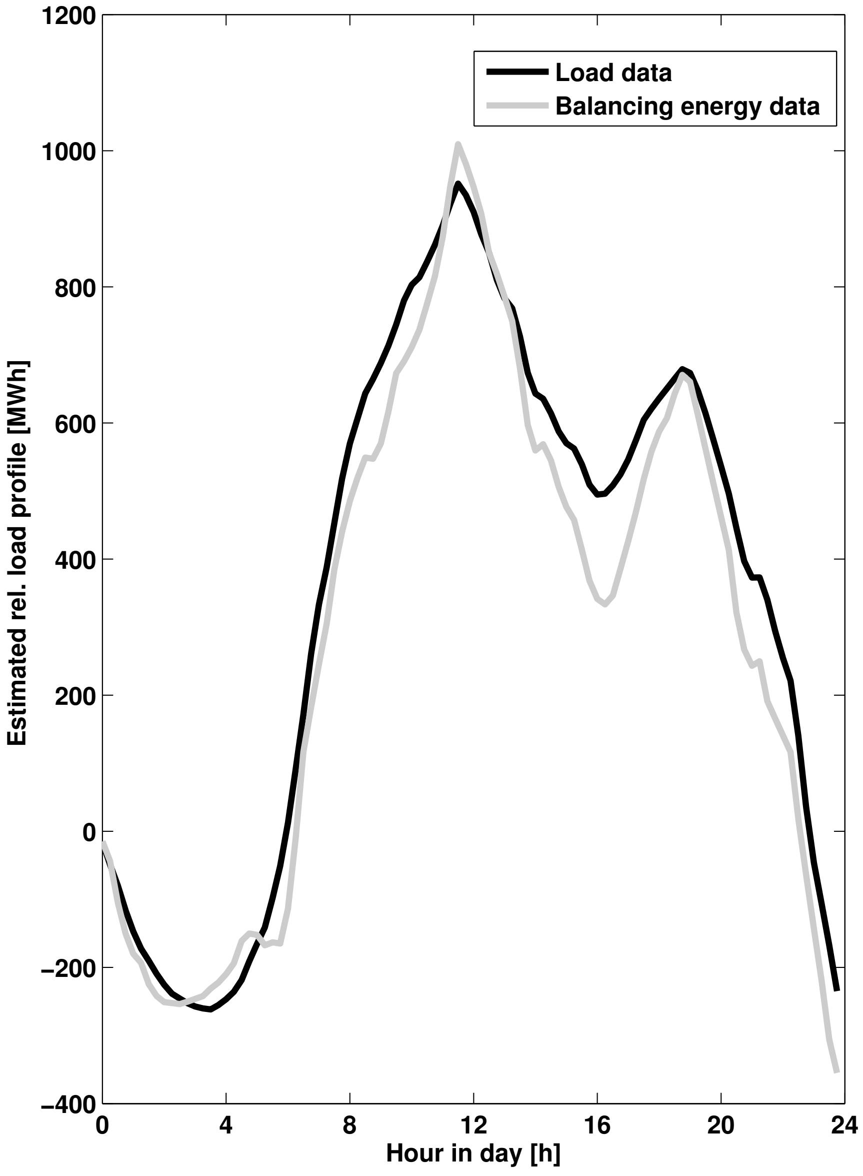


Figure 4.2: Comparison of model (dark) and scaled data (light) using 2004 data.



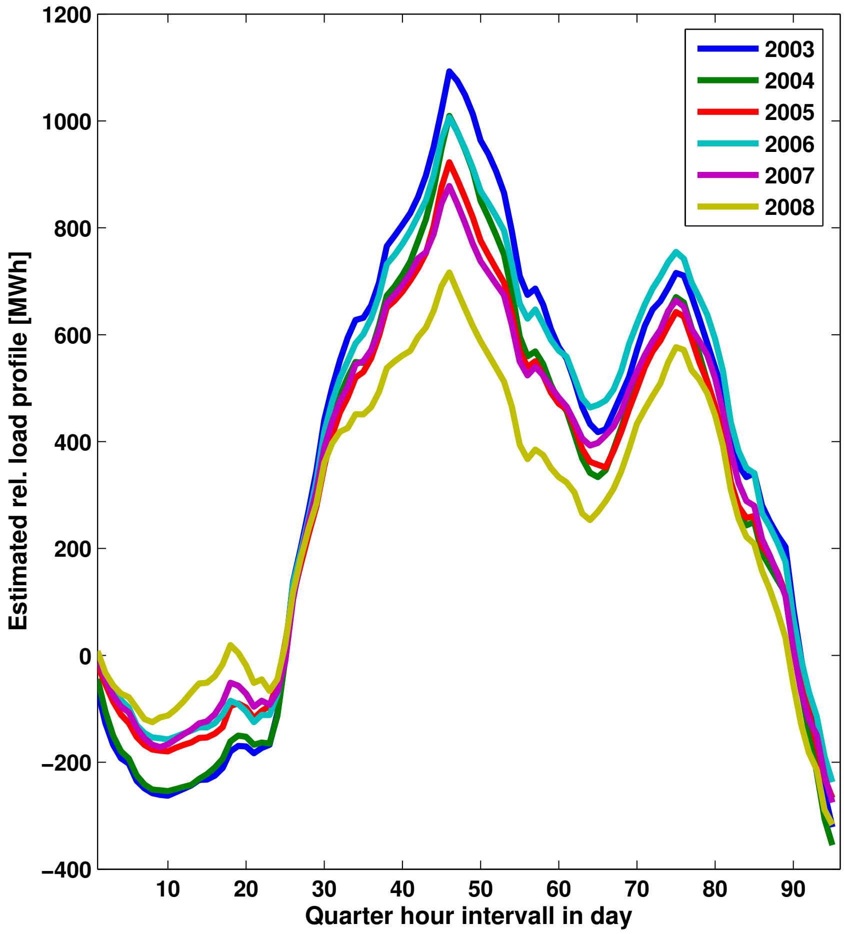
are used to predict the other patterns in this group in an out-of-sample analysis as shown in Table 4.1. The high R^2 values indicate the consistency of the quarter-hourly pattern. Moreover, the explanatory power tends to be higher for subsequent years demonstrating that this simple factor captures aspects not included in the gradient model in equation (4.2). When using the pattern of the total sample and an additional scaling factor to predict the yearly patterns, a diminishing amplitude of the quarter-hourly pattern is observed as can be seen in Table 4.1. This finding is supported by Figure 4.3 which displays the patterns of hourly line segments joined into daily patterns for illustration. In comparison to the gradient model, the prediction of the quarter-hourly pattern by the out-of-sample pattern of the preceding year reaches an even higher accuracy. This predictor better incorporates technical issues such as the flattening between interval 20 and 24, and therefore lends itself for modeling. However, one should bear in mind that this modeling is vulnerable to a change in the shape of the load profile. The gradient model is based on a more general understanding and can therefore be employed in such situations.

4.3.2 Incentive for the quarter-hourly pattern

It is important to note that the quarter-hourly pattern is driven by the consumption side of the market rather than the production side. Overall it can be said that the production side follows the step function dictated by hourly contracts, while the consumption changes gradually. This brings about the quarter-hourly pattern. As there is no liquid market to trade electricity with sub-hourly delivery periods in Germany, there is practically no way to avoid the quarter-hourly pattern. For this reason BRPs that are positively correlated to the load pattern (consumers) incur additional cost, while BRPs that are negatively correlated to the load pattern (producers) have a financial gain. So there is an economic incentive for BRPs to redistribute part of its load within an hour and obtain a negative correlation to the quarter-hourly pattern for that part of its load. Such a strategy is equivalent to buying electricity during periods with an expected lower net deviation and price, and selling it at higher prices during periods with an expected higher net deviation.

The described strategy results in an intervention similar to that of reserve capacity and aids network stability. So, on a quarter-hourly time frame the balancing energy market is an alternative marketplace to the capacity reserve market. However, in contrast to the capacity reserve market there are no pre-qualification standards. Also, there is no fixed compensation but rather a statistical-arbitrage return. Consequently, the balancing

Figure 4.3: Shape of the load curve as estimated from quarter-hourly balancing energy data



energy market will also attract additional capacity which is not tradable on the capacity reserve market. In fact, the diminishing amplitude of the quarter-hourly pattern is an indication of market participants recognizing and exploiting the balancing energy market in this manner. In Chapter 5 these ideas are developed further.

4.4 Hourly pattern

By definition the quarter-hourly pattern will always average to zero over the four intervals of an hour. Consequently, the quarter-hourly pattern has no implications on electricity spot prices. However, on an hourly time frame the balancing energy market is an alternative marketplace for the electricity trades in the day-ahead market and contracts in the capacity reserve market. (See Section 2.3). To investigate the balancing energy data on this time frame the data is integrated to hourly values, which correspond to the hourly contracts traded in the day-ahead market. All subsequent analysis is based on these hourly balancing energy data. Furthermore, it is assumed for simplification that the day-ahead market is in equilibrium with the other marketplaces including the capacity reserve market. (See Wieschhaus and Weigt, 2008). Therefore, the general market can be represented by the day-ahead market prices only.

4.4.1 Describtion and incentive structure

As introduced in Section 2.1, there is a fundamental weekly seasonality in the German electricity market, as shown in Figure 2.1. To match this seasonality a weekly pattern from the balancing energy data is extracted using the following approach. For each day of the year a symmetric time window of seven weeks is applied, and the balancing energy data are aggregated over the years 2003-2008. The pattern is then estimated by the average demand conditional on the hour within a week. The resulting hourly pattern is presented in Figure 4.4. When compared to the load in Figure 2.1, a similar seasonality is inherent in the balancing energy demand matching the seasonal characteristics of the load in many details. The hourly balancing energy pattern is capturing both the weekly peak and off-peak shape, and the summer-winter dependence, well characterized by the presence of an additional pronounced demand peak during evening hours in the winter months. The presence of this pattern is clearly incompatible with all BRPs providing a balanced minimum-variance forecast because such forecasting should result in a purely random pattern of conditional expectation values. In general, the observed hourly positions result either from a reluctance of market participants to provide balanced forecasts, or they indicate intentional strategic behavior. An inadequate consideration of transmission losses and a load-dependent risk of failures could be the reason behind the former. The latter is linked to statistical-arbitrage incentives between the balancing energy market and the day-ahead market. As outlined in Section 2.1 these strategic positions result in a cost reflective preliminary schedule. While it is impossible to disregard the reluctance of market participants, the following analysis demonstrates that the detected positions are at least partially of strategic nature.

To test the continuity of the hourly pattern yearly patterns are calculated. In an adaption of the approach used for the hourly pattern, the data are averaged over summer and winter months. Consequently, the resulting patterns will not uncover the summer-winter dependence. However, individual years can be compared by using the out-of-sample average pattern for each year as a prediction for the in-sample pattern. The results are presented in Table 4.2. With the exception of 2004, this simple one factor model has reasonable predictive power. A further inspection of the prediction error in 2004 shows the prediction is capturing the general shape well. However, it overestimates the amplitude. This finding is supported by an in-sample fit of a scale parameter to the out-of-sample pattern reported as R^{2^*}. The scale parameter of 2004 is almost halved. Reluctance does not explain such sudden changes in the observed pattern as it would change gradually if at all. So this reduced scale indicates a change in strategic positions in the balancing energy market. Moreover, 2004 was a year with an exceptionally low number of electricity price spikes in the day-ahead market. In this context the absence of spikes reduces the statistical-arbitrage incentive between the balancing energy market and the day-ahead market, and may explain the change in amplitude of the hourly pattern. This hypothesis of an adaption to a varying statistical-arbitrage incentive is tested in the following discussion that considers the arguments on balancing energy demand and day-ahead prices in Section 2.3 further.

German balancing energy prices depend on the prices of secondary and tertiary capacity reserve and the balancing energy demand. Furthermore, the prices of capacity reserve reflect only the small fraction of readily adjustable installations. In contrast, the price in the day-ahead market reflects the supply and demand equilibrium of the full merit-order-curve at an hourly time scale. In addition, demand remains the sole determining factor of balancing energy prices responsive on an hourly time frame because secondary and tertiary reserve capacity prices involve longer contractual periods of one month and four hours respectively.

Consequently, market participants have an economic incentive to con-

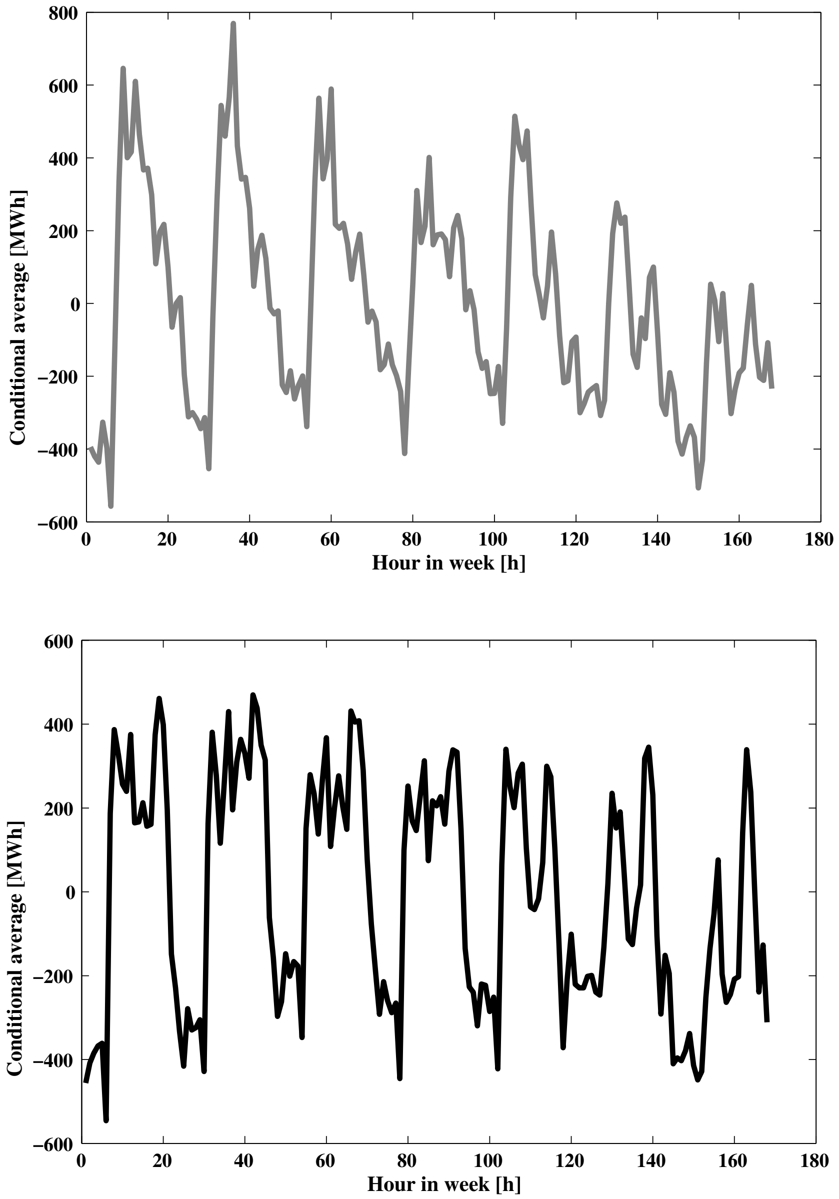
Table 4.1: R^2 using yearly quarter-hourly pattern and scaled total quarter-hourly pattern for prognosis. R^2 values significant at the 0.1% significance level.

	Predictor pattern	Year					
		2003	2004	2005	2006	2007	2008
R^2	2003	-	0.9853	0.9074	0.9413	0.8867	0.7830
	2004	0.9865	-	0.9393	0.9520	0.9130	0.8427
	2005	0.9396	0.9569	-	0.9738	0.9681	0.9329
	2006	0.9538	0.9588	0.9683	-	0.9775	0.9260
	2007	0.9243	0.9367	0.9673	0.9809	-	0.9703
	2008	0.8746	0.9010	0.9405	0.9457	0.9743	-
	Total_{scaled}	0.9820	0.9861	0.9896	0.9909	0.9866	0.9667
$\text{Scale}_{in-sample}$		1.1478	1.1025	0.9301	1.0229	0.9405	0.8657

Table 4.2: R^2 using out-of-sample average and scaled out-of-sample average for the prediction of the hourly pattern. R^2 values significant at the 0.1% significance level.

Year	2003	2004	2005	2006	2007	2008
R^2	0.7857	0.2003	0.7435	0.7712	0.8316	0.8492
R^{2^*}	0.7863	0.6229	0.8019	0.8286	0.8381	0.8536
$\text{Scale}_{in-sample}$	0.9733	0.5483	0.7874	1.3570	1.0961	1.0772

Figure 4.4: Weekly balancing energy pattern (Monday to Sunday) in summer (light) and winter (dark) (hourly pattern)



sume more of the risky but evenly priced balancing energy as demand and prices on the day-ahead market rise. Therefore, an hourly pattern in balancing energy should resemble the load profile. This represents an superior preliminary schedule under the condition of demand uncertainty as compared to a preliminary schedule with no strategic position in the balancing energy market. In practice, market participants would exercise their grid excess as a real option when electricity prices are high as long as balancing energy is expected to have a favorable price (i.e., until the two markets reach an equilibrium). It should be stressed that exploiting this spread between day-ahead market prices and expected balancing energy prices is a statistical-arbitrage opportunity as balancing energy prices are uncertain at the time a position is entered.

To capture this incentive for strategic positions in the balancing energy market a factor $(I(t))$ is introduced . This factor is defined by the difference of day-ahead prices from the current price level. As a specification of the price level the median price of the preceding four weeks is used. The time span of four weeks is chosen in an effort to balance stability and slackness considerations in the definition of a price level. This is supported by testing other multiples of weekly time spans that did not change the substance of the results. However, the median was explicitly chosen to create a spike-insensitive measure for the price level, so that the defined factor will capture price spikes.

The marks in Figure 4.5 show the mean balancing energy demand conditional on the factor value. Here, the balancing energy demand is measured relative to a long-term mean level of four weeks. This separates effects of longer time duration that are discussed in Section 4.5. Each individual year in the dataset is displayed demonstrating an overall continuous structure. The dependence structure reaches from a central linear domain into a domain of saturation at higher factor values. The effect of saturation is to be expected in view of the limited reserve capacity the grid operator provides. These constraints are reflected by balancing energy prices and enforced in grid access contracts. (See Appendix B). In principle, these findings apply as well to all four control areas individually as can be seen in Figure 4.6. However, the data cannot account for balancing activity between control areas. Such effects are excluded by netting all four control areas, and therefore the further investigation is restricted to the hypothetical combined control area that corresponds to the single German day-ahead market.

Figure 4.5: Factor value ($I(t)$) and hourly balancing energy demand

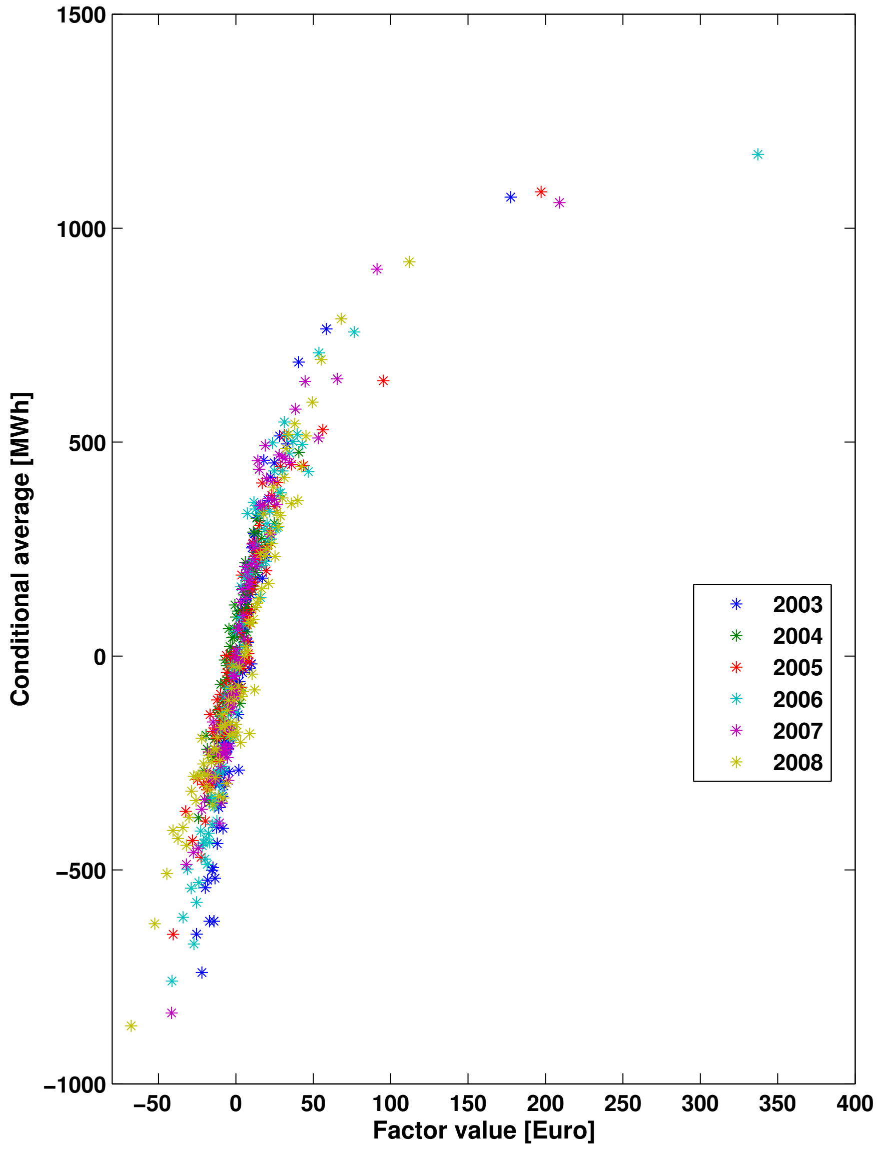
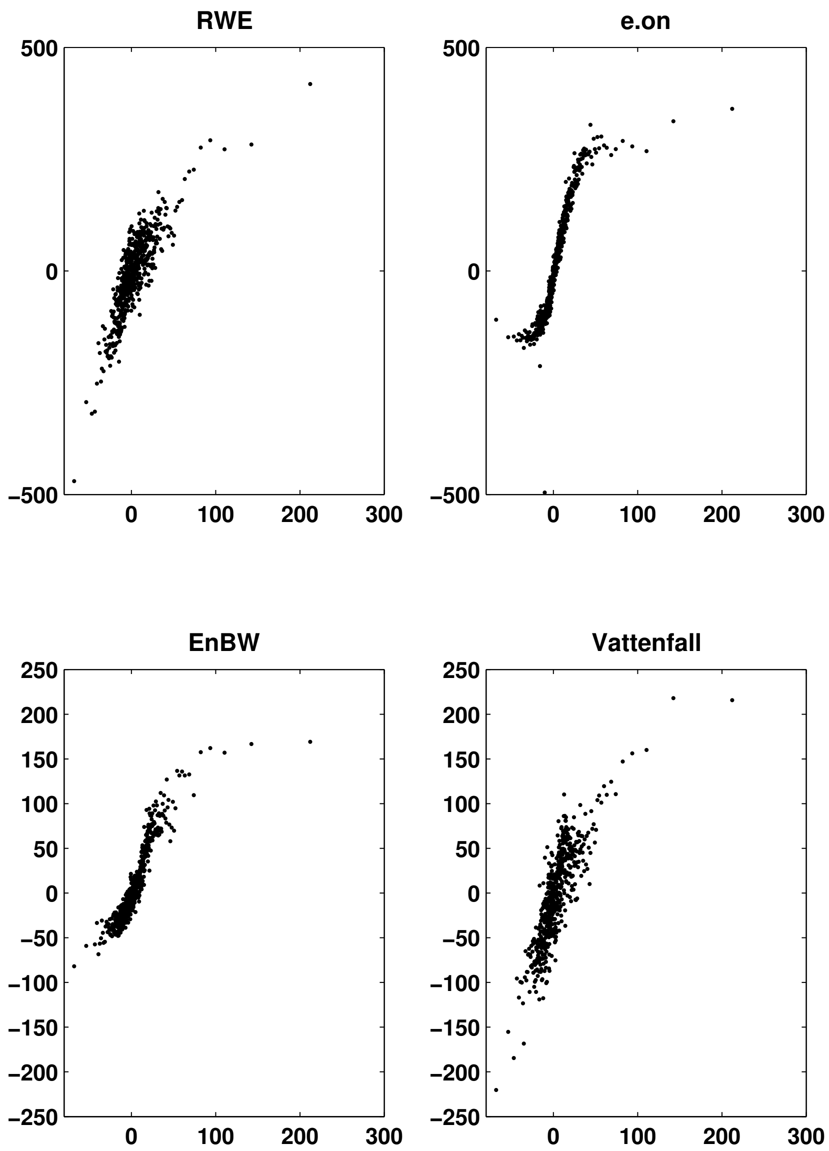


Figure 4.6: Conditional average hourly balancing energy demand versus factor value ($I(t)$) in the four German control areas



4.4.2 Factor model

A three-parameter factor model is proposed for the hourly balancing energy deviation pattern (see first summand in equation (4.3)):

$$h(I(t), I_{tec}(t)) = a \cdot \left(\frac{2}{1 + b \cdot e^{-c \cdot I(t)}} - 1 \right) + I_{tec}(t) \ \forall a \in \mathbb{R} b, c \in \mathbb{R}_+ \quad (4.3)$$

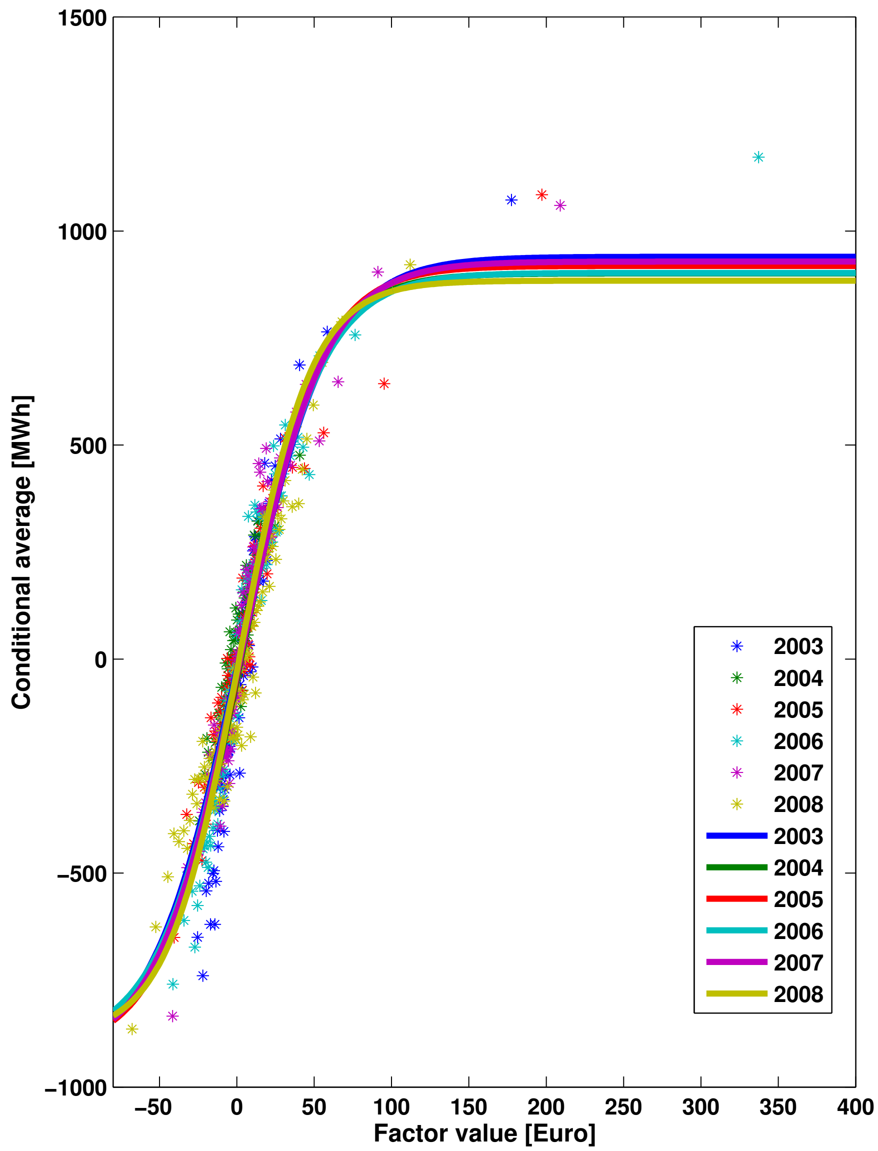
Figure 4.7 and Table 4.3 show parameter estimates from out-of-sample fits for each year and corresponding R^2 values. Evidently, the dependence structure is constant over time. Moreover, this factor model captures the change in amplitude that in imposed by less volatile electricity prices in 2004.

When compared to the R^2 values in Table 4.2, the factor model does not seem to explain the hourly pattern fully. A further inspection of the residual pattern shows the change in amplitude for the year 2004 to be captured well, but some pronounced seasonal effects remain. One such example is a highly negative balancing energy demand between five and six at weekday mornings. As discussed in Section 4.3 this coincides with peak units synchronizing and going online to cover the following steep ramping hours. In this view the oversupply in the first half of the hour is explained by the positive load gradient, while the oversupply in the second half is related to power stations synchronizing with the grid frequency and starting to feed-in electricity ad minimal capacity. Through this combination the hour five to six in the morning is on average in constant oversupply.

To include such technical effects that will be constant over time, the out-of-sample weekly average pattern is used as an additional factor ($I_{tec}(t)$). The resulting combined model in equation (4.3) can explain much of the detected seasonal variation. (See Table 4.3.) Also, when compared to the R^{2^*} values in Table 4.2, the combination of statistical-arbitrage incentive and technical effects shows similar predictive power. However, the latter model does not resort to in-sample information. Using this out-of-sample prediction, the variance of the hourly balancing energy data is reduced by 19.2%.

The detected hourly pattern can be modeled by equation (4.3). While the I_{tec} component in this model is compatible with a reluctance of market participants to provide a balanced forecast, the contribution of the statistical-arbitrage incentive is evidence of strategic balancing energy deployment. Clearly, market participants recognize and implement the statistical-arbitrage opportunities between the day-ahead market and the balancing energy market in their portfolio management. Such strategies result in a lower than average amplitude of the hourly balancing energy pattern in years with less than average electricity price spikes as 2004.

Figure 4.7: Factor model ($I(t)$) prediction (solid lines) and data (asterisk). R^2 values significant at the 0.1% significance level.



4.5 Long-term pattern

After a few of their respective cycles, the average of both the quarter-hourly pattern and the hourly pattern is zero. In fact, in Section 4.3 and 4.4 these patters are by definition referenced to the average value on a longer time frame. This guarantees the separation of effects on the different time scales. In order to complete the analysis, positions in the balancing energy market that are persistent over longer periods of time are investigated. These positions are extracted from the residuals of the hourly factor model in equation (4.3), by application of a seasonal autoregressive integrated moving average (SARIMA) model as applied in similar setting by Olsson and Söder (2008).

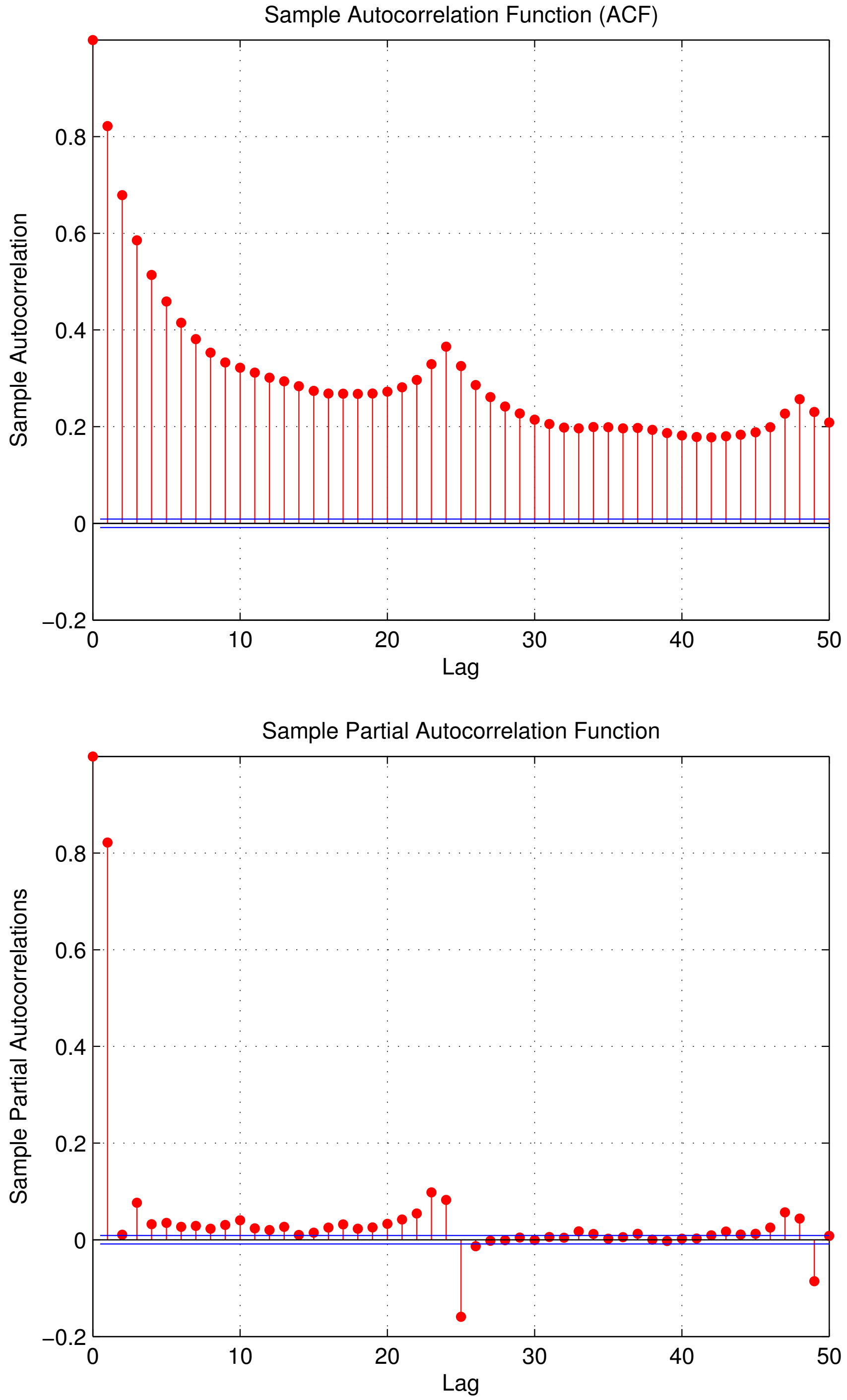
4.5.1 SARIMA model of residuals

To adapt a linear time series model to the residuals, the data need to be checked for stationarity. For this an augmented Dickey-Fuller unit root test is employed. The null hypothesis of a unit root is rejected at a significance level below $\alpha = 0.001$ even when including the first 168 lags for the regression and stationarity is accepted.

This finding is supported also by a consideration of the physical boundary conditions of the underlying data. Balancing energy demand is fulfilled by the TSO to ensure grid balance. This energy has to be delivered physically by power stations. Thus, the installed capacity imposes a hard boundary. This boundary can, however, never be reached because the response time and response capacity of power stations impose an even tighter boundary. Due to their design powers stations cannot run on an arbitrary fraction of their designed capacity, but have to be operated within a certain bandwidth instead. Additionally, a complex system such as a power station has a considerable amount of inertia, and cannot instantaneously adapt to changes in operation. When looking at the total generation stock, these facts do not translate into a hard boundary. Instead, the true limits depend on the exact condition and history of all individual facilities connected to the grid. Nonetheless, a limit to fluctuations the TSO can manage always exists. Consequently, it is physically impossible for the balancing energy demand to grow to very large positive values or to fall to very small negative values. On the contrary, balancing energy will always be within a bandwidth around zero. Mathematically, this argument relates to a stationary time series, and the absence of unit roots. The residuals can therefore be modeled without the need of further differencing.

As a first step an inspection of the SACF and SPACF of the residuals in Figure 4.8 shows the presence of SARIMA effects in the data. The

Figure 4.8: Sample autocorrelation and partial autocorrelation



autocorrelation decays off with increasing lag. Additionally, this decay is disturbed at multiples of 24 indicating a seasonality of 24 hours. This is supported by the partial autocorrelation function displaying a drop at lag one and 24, together with a decaying negative partial autocorrelation at lags following multiples of 24. Moreover, the SPACF indicates another step at lag three. Therefore the multiplicative models SARIMA$(1,0,0) \times (1,0,1)_{24}$ and SARIMA$(3,0,0) \times (1,0,1)_{24}$ are chosen as candidates for the model. In addition to the classical model with Gaussian innovations, models with t-distributed innovations are included as representatives of heavy-tailed innovations in the analysis. This is the standard approach suggested by Zumbach (2006). It provides a compromise between a heavy-tailed innovation distribution and robust parameter estimation for the SARIMA model. Table 4.4 holds the AIC and BIC values of different specifications including both Gaussian and t-distributed innovations. The SARIMA$(1,0,0) \times (1,0,1)_{24}$ model with t-distributed innovations is chosen for two reasons. First, the AIC and BIC values indicate a preference of t-distributed innovations over the Gaussian case. Second, the TSO's information disclosure to market participants is several days to a month. Therefore, the low-lagged coefficients are of minor practical relevance in the context of this analysis because their effect decays off rapidly and cannot be utilized on a relevant time frame. The ar_3 coefficient is consequently disregarded. Note that the suggested t-distributed innovations demonstrate the necessity of a heavy-tailed noise term in the model. This reflects the importance of unpredictable extreme events for the balancing energy demand as will be further investigated in Section 4.5.3.

To conclude this section, an analysis of the consistency of the model over time and a test of the validity of its forecasts is performed. Table 4.5 reports the parameter estimates of the model based on yearly sub-samples. The parameter estimates are consistent with the overall model. It is therefore decided to test the forecasts of the overall model rather than the individual yearly models.

As stated above, the TSOs do not reveal the information on balancing energy demand to the market continuously, but rather publish the data for the preceding month once a month. So the data for May will be available by July. Therefore, it is of no practical relevance to test the one-time step forecast because this has no practical implication in the given market design. Instead, a forecast horizon adapted to the information revealed to the market is tested. As a result forecasting is performed once a month based on the information lagged one month (i.e., the forecast horizon is 720 to 1,440 lags). Additionally, a forecasting horizon of three days is tested because one of the TSOs also publishes the balancing demand data in its control area with this time delay (i.e., a forecast horizon of 72 to 96 lags). In both cases, the sample variance is reduced by subtracting the conditional expectation. When using the monthly forecast, the variance is reduced by 3.69%. Applying a three-day forecast horizon results in a 11.22% reduction.

Based on the model coefficients, this additional variance reduction as compared to the analytical model in Section 4.4 can be decomposed into two components. The first component represents comparatively short-lived patterns in the data. These patterns can be understood as a linear correction term for the analytical model. The second component captures a non-zero conditional mean of the time series. This component is in the focus of this section and represents a long-term position in the balancing energy market. Neither the gradient effect nor the statistical-arbitrage incentive described in Section 4.3 and Section 4.4 can account for such positions because they are defined to average to zero over a few cycles of their respective seasonality. However, when looking at the average forecast of the SARIMA model in Table 4.6, it is evident that the SARIMA forecast does not average to zero over a few cycles, but displays a long-term pattern in the balancing energy demand.

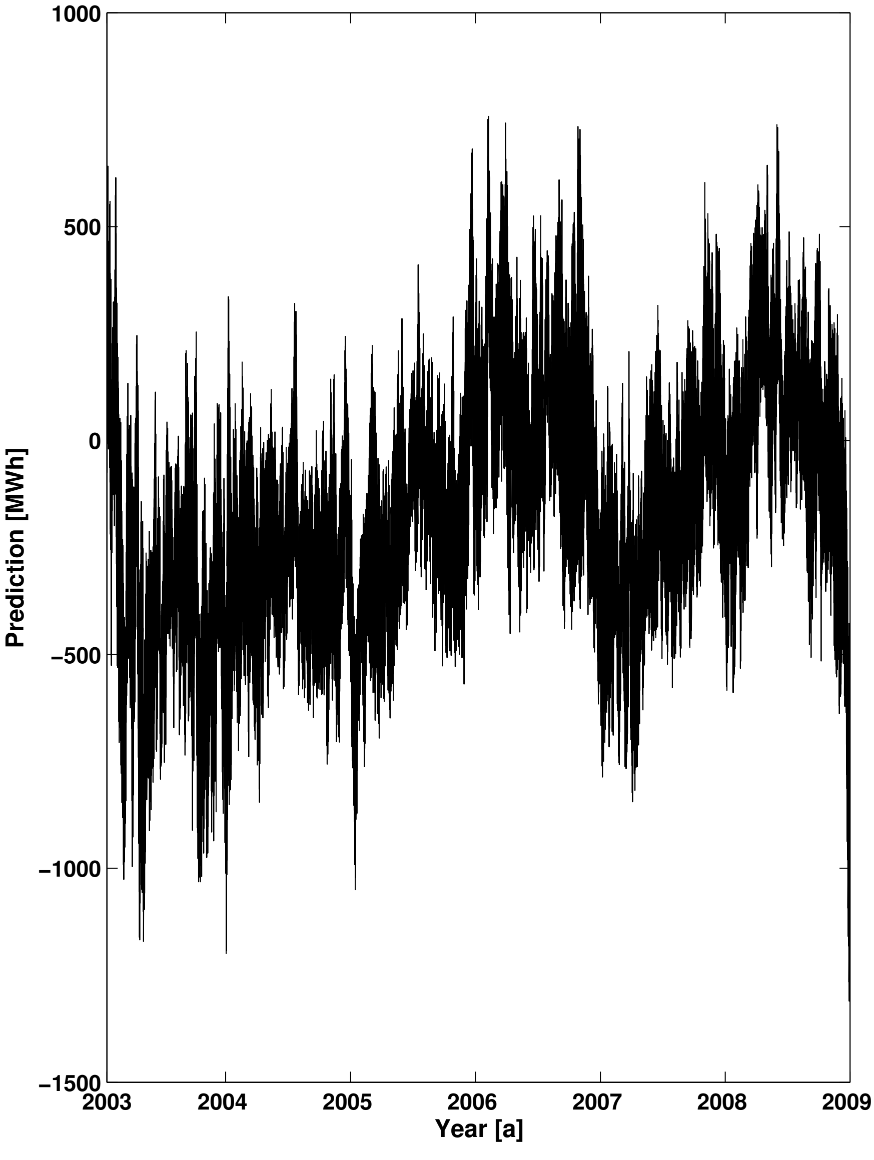
4.5.2 Incentives for long-term positions

In this section these results are considered in the context of electricity portfolios. Market participants use the balancing energy market not only for short-term adjustments to their portfolio as in the hourly pattern, but also take positions over extended periods of time. This is supported by the result displayed in Figure 4.9 that shows the timely evolution of the three-day forecast. It clearly displays the predictable long-term offset in the balancing energy demand. The magnitude and the sign of this offset vary over the years. This finding persists even in the case of the long forecast horizon of a month. Thus, this offset cannot be attributed to a lack of information, and the change in amplitude and sign indicates intentional positions.

As in the case of the hourly pattern, a long-term position in the balancing energy market coincides with a countering position in the futures market. Specifically, the day-ahead futures market serves as a reference in this analysis. From this perspective, the price of the deviation is the difference between the balancing energy price and the day-ahead market price. In other words, a positive deviation can be described as a short position in a day-ahead contract, and a long position in the balancing energy market, and vice versa for a negative deviation. In turn, the cost of deviations are obtained by multiplying price and volume, and the cost function can be approximated by the average cost for a given deviation.

Figure 4.10 shows the estimated cost function in the different control

Figure 4.9: Prediction values with a three-day lag in information disclosure



areas using 2003-2008 as the sample data. At a deviation close to zero, the cost increase linearly indicating a constant price. However, the cost function levels for large negative deviations, whereas it increases drastically at large positive deviations. Considering strategic long-term positions in the balancing energy market, this asymmetry in the cost function is an important point. For a given forecasted distribution of an electricity portfolio such positions shift the location parameter of the distribution, while scale and higher moments will not be affected. Under the described cost function, shifting the deviation towards the negative (i.e., a surplus of day-ahead contracts) will continuously incur cost from additional negative deviation. At the same time this shifting reduces the risk of high cost at high positive deviation. So given an unavoidable uncertainty in the portfolio or forecasting error, a negative net position is a rational response to the observed cost function.

For further inspection of the linear domain, the analysis is concentrated on the largest control area in terms of load, the RWE control area. The cost functions of individual years are estimated as displayed in Figure 4.11. Evidently, the slopes of the cost function vary. Particularly interesting is the difference in slope for positive and negative deviations within individual years. A difference in slope provides an incentive to move deviation risk towards the flatter side of the cost function in order to reduce cost. In the example of the RWE control area the cost functions for the years 2005 and 2006 indicate an incentive to shift deviation towards the positive. For the other four years investigated a negative net deviation would have been profitable. Finally, the opening angle between the linear domains at the positive and the negative branch of the cost function varies. Here, a wider opening angle will incur less cost for a strategic deviation.

Using these arguments, the increasing long-term position in 2005, 2006, and 2008 (see Figure 4.9) is an adequate adaption to a cost function tilting towards positive deviations. In the cases of 2003, 2004, and 2007, a negative position coincides with a cost function tilted towards negative deviations. Additionally, the opening angle of the cost function narrowed in 2008 providing an incentive to reduce strategic positions.

A complete investigation should include all four control areas. However, there is no balancing energy price for the net deviation of all four control areas to base such an analysis on. Nonetheless, these findings demonstrate that there are economic incentives behind the detected long-term balancing energy positions. With its asymmetric cost function for the balancing energy, the German market design appears being prone to push market participants to a strategic short position in the balancing energy market. These positions have to be countered by a long position in the futures markets. In

Figure 4.10: Cost of deviation conditional on deviation [€] versus deviation [MWh] in the four German control areas

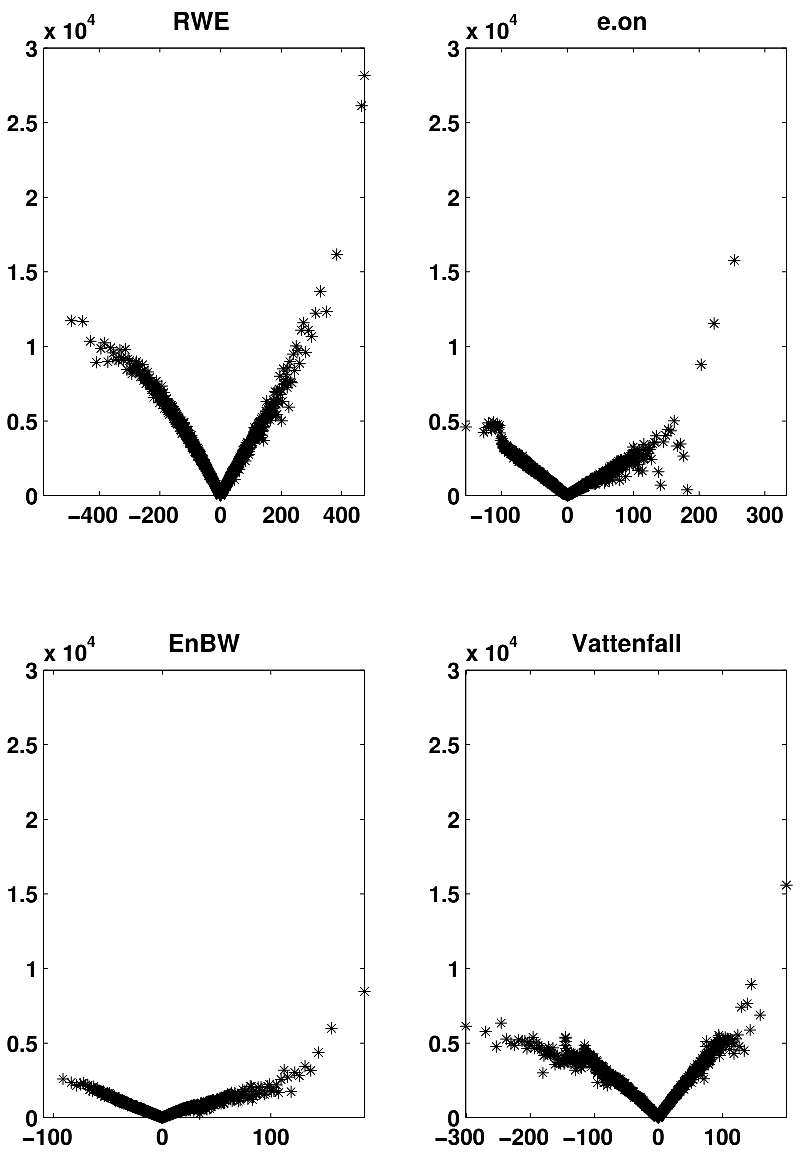
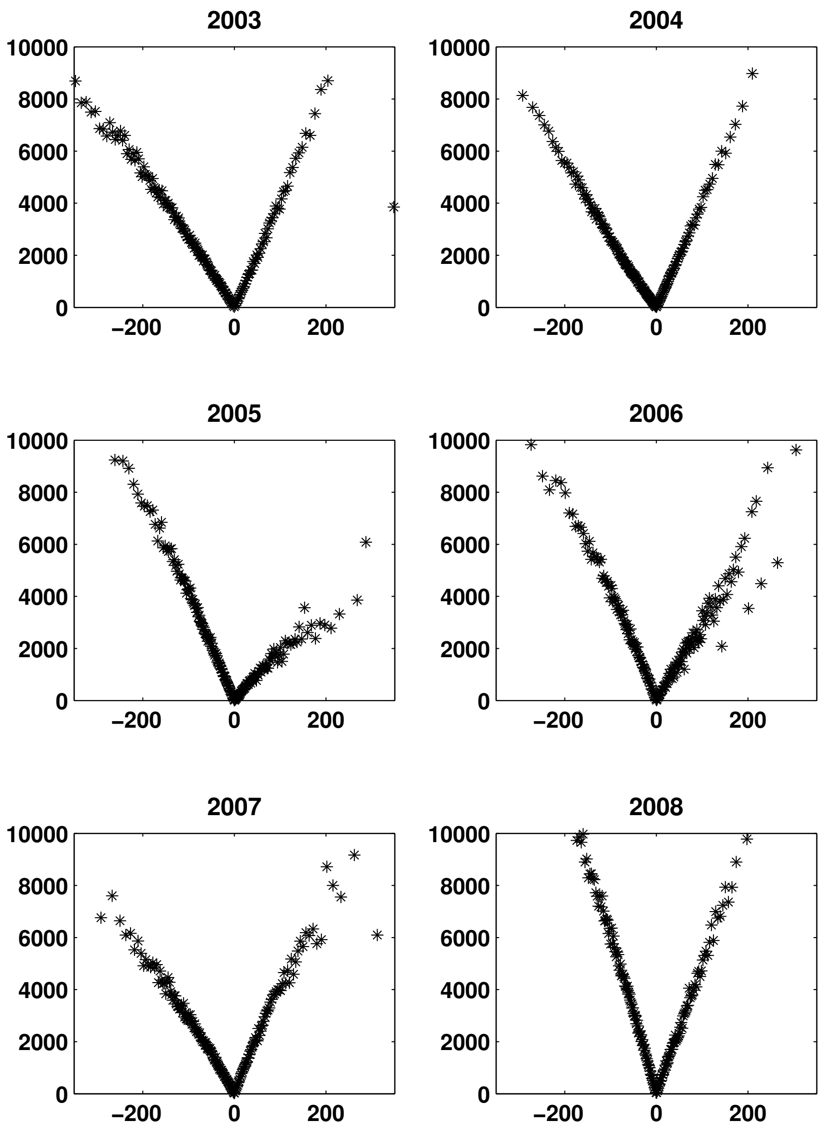


Figure 4.11: Empirical cost function of deviation [€] versus deviation [MWh] in the RWE control area from 2003 to 2008



other words, the German market design creates a virtual demand in the day-ahead market.

4.5.3 Innovation distribution

The parameter estimation of the SARIMA model used in Section 4.5.1 is based on a t-distributed innovation process. Models with Gaussian innovations were rejected based on AIC and BIC values reported in Section 4.5.1. In the following, the analysis is completed by the identification of the innovation process that is crucial for an assessment of associated risks. Therefore, the identified heavy-tailed innovation process is investigated further.

The innovation process is of particular importance in the balancing energy market as it governs the risk involved in balancing the network. In general, TSOs have to allocate sufficient capacity reserves to be able to maintain grid operation and avoid a blackout. The capacity that is considered sufficient is usually defined by a threshold probability for a blackout (i.e., the probability of fluctuations exceeding the allocated capacity). The more precise the quantiles of the innovations' distribution are known, the more efficiently resources may be allocated. In addition, the balancing energy demand is a key risk factor in the patterns discussed in this chapter. Therefore, the innovations' distribution is of high relevance with respect to the risk of the corresponding strategies.

The first step of the investigation is the QQ-plot of the innovations' time series and the fitted t-distribution in Figure 4.12. From this figure it can be seen that the t-distribution does not adequately capture the risk in the tails of the empirical distribution because the QQ-plot deviates from the diagonal.

Due to the conceptual advantage of modeling data with a distribution in the proximity of the gCLT as discussed in Section 3.2, both the α-stable and the CTS-distribution are tested as more adequate models for the innovations' time series. Both distributions are estimated by the Fourier inversion formula and their characteristic functions given by equations (3.9) and (3.10). This inversion is in turn numerically estimated by the fast Fourier transform (FFT) method. A more detailed description of the method is given in Nolan (1997) and Kim *et al.* (2009). Table 4.7 shows the estimated parameter sets. As can be seen in Figure 4.13, the heavy-tailed distribution captures the likelihood of extreme events more accurately than the t-distribution.

In the next step, all three distributions are compared using the goodness-of-fit tests mentioned in Section 3.2.4. The results are summarized in Table 4.8.

The p-values of the KS-test clearly indicate that the CTS-distribution

Table 4.3: Hourly pattern: parameters and R^2 fitting to out-of-sample data

	Parameters			R^2 factor model	
Year	$a[MWh]$	$b[E]$	$c[1/€]$	$I(t)$ only	$I(t)$ and $I_{tec}(t)$
2003	940.045	1.053	0.035	0.6948	0.7252
2004	901.082	1.113	0.039	0.4448	0.6170
2005	918.633	1.089	0.039	0.6069	0.7518
2006	902.485	1.072	0.038	0.8424	0.8499
2007	928.798	1.081	0.037	0.7571	0.7998
2008	884.110	1.068	0.043	0.6530	0.7025

Figure 4.12: QQ-plot t-distribution

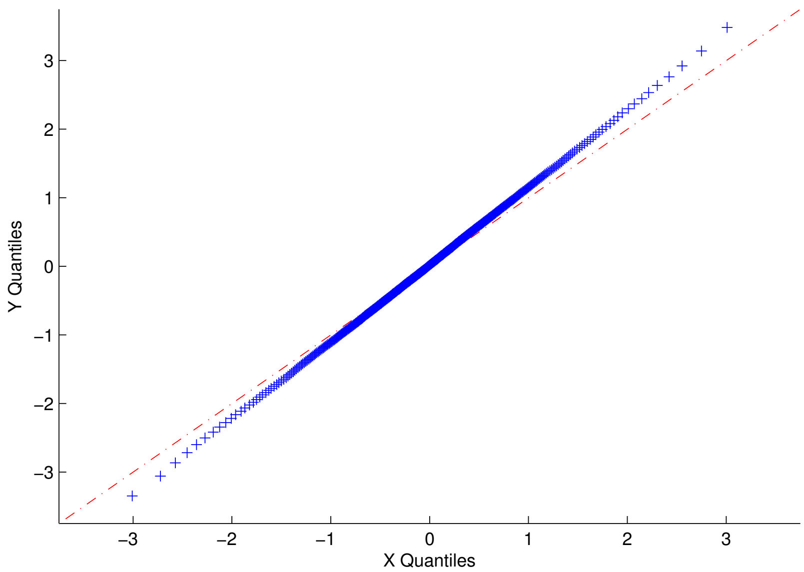


Table 4.4: Parameter estimates of the SARIMA model

	SARIMA			
	$(1,0,0)\times(1,0,1)_{24}$		$(3,0,0)\times(1,0,1)_{24}$	
	Gaussian	t(ν)	Gaussian	t(ν)
ar_1	0.8185	0.8238	0.7974	0.8036
ar_3	-	-	0.0084	0.0079
ar_{24}	0.9572	0.9571	0.9419	0.9427
ma_{24}	-0.8502	-0.8529	-0.8291	-0.8328
σ	341.9658	341.9410	341.7744	342.0834
ν	-	9.1080	-	9.1396
AIC	763,170	762,080	763,060	761,970
BIC	763,200	762,110	763,090	762,000

Table 4.5: Parameter estimates of the SARIMA model

Parameter	a_1	a_{24}	b_{24}	σ	ν
total	0.8238	0.9571	-0.8529	341.9410	9.1080
2003	0.8522	0.9307	-0.7973	341.9410	9.4983
2004	0.7860	0.9421	-0.8184	328.8776	12.3724
2005	0.7810	0.9359	-0.8248	325.6431	10.7623
2006	0.8092	0.9455	-0.8397	336.8019	9.0538
2007	0.8067	0.9586	-0.8620	329.9785	10.1529
2008	0.7861	0.9515	-0.8541	341.9410	9.2676

describes the innovations best because its p-value is 49 and 9 orders of magnitude greater than the p-value of t-distribution and α-stable distribution, respectively. However, the p-value of the CTS-distribution is still low. As discussed in Section 3.2.4, the KS-test is responsive to small fluctuations in the location parameter. Though such fluctuations are to be expected with heavy-tailed distributions. Thus, the SARIMA model implies a location parameter of zero for the innovation process, so the test does not need to focus on the location parameter. Therefore, the mean of the innovations' time series is corrected for such fluctuations within the 95% confidence bounds. The corresponding statistics are identified by an asterisk (*). Again, the CTS-distribution provides the best description of the data. Furthermore, the CTS-distribution is accepted at a 5% significance level. The other statistics reported provide further support for choosing the CTS-distribution over both the t-distribution and the α-stable distribution.

Table 4.6: Average prediction of the SARIMA model

	Average prediction [MW] at horizon	
Year	One month	Three days
2003	-198.9537	-372.3728
2004	-179.9403	-307.2270
2005	-110.6992	-214.6126
2006	21.8594	18.6222
2007	-118.4479	-217.6485
2008	-52.1579	-190.4806

Table 4.7: Estimated parameters of heavy-tailed distributions

Distribution	Parameters				
α-stable	α	σ	β		μ
	1.9107	0.0048	0.6711		0-fixed
CTS	α	C	λ_+	λ_-	m
	0.9122	$\frac{1}{\Gamma(2-\alpha)(\lambda_+^{\alpha-2}+\lambda_-^{\alpha-2})}$	1.4856	1.5168	0-fixed

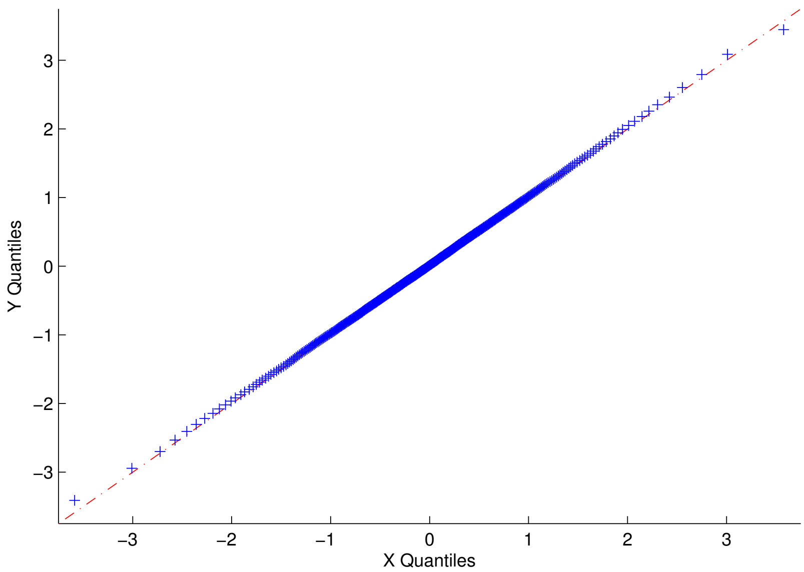
The identification of the CTS-distribution underlines the importance of heavy-tailed phenomena in the balancing energy data. It shows that extreme events effect the balancing energy demand on an hourly time frame. Moreover, the distribution in the proximity to the α-stable distribution causes the influence of extreme events to prevail over long time frames. At the same time, the rejection of the α-stable distribution indicates that events in the fare-tails are improbable. In fact, the sample contains missing data in the year 2006, when a black-out disturbed the system operation in some control areas. In other words, the balancing energy demand is limited by physical boundray conditions as indicated by the CTS-distribution.

Concluding, the results of this section are combined to one model of the long-term balancing energy demand in equation (4.4) defined on the residual hourly data ($D_{B_{res}}$):

$$\begin{aligned} f(t) &= 0.8238 \cdot D_{B_{res}}(t-1) + 0.9571 \cdot D_{B_{res}}(t-24) \\ &-0.7885 \cdot D_{B_{res}}(t-25) - 0.8529 \cdot \sigma(t-24) + \sigma(t) \\ where\ \sigma(t) &\sim 341.9410 \cdot CTS(0.9122, 0.3410, 1.4856, 1.5168, 0) \end{aligned} \tag{4.4}$$

In combination with equation (4.3) this is the proposed model for the German balancing energy demand in hourly resolution. It is important to note

Figure 4.13: QQ-plot CTS-distribution



that equation (4.4) is only valid in combination with the model of the hourly pattern. A direct SARIMA modeling could not capture the dynamics of and the non-linear dependence on the statistical-arbitrage incentive discussed in section 4.4.

Table 4.8: Goodness-of-fit statistics and p-values

	Distribution					
	t		α-stable		CTS	
Test	Statistic	p-value	Statistic	p-value	Statistic	p-value
KS	0.0331	$1.37 \cdot 10^{-50}$	0.0156	$1.75 \cdot 10^{-11}$	0.0082	0.0016
AD	0.0883	-	0.0333	-	0.0170	-
KS*	0.0316	$5.73 \cdot 10^{-46}$	0.0134	$1.40 \cdot 10^{-8}$	0.0059	0.0538
AD*	0.0854	-	0.0316	-	0.0126	-
CvM*	23.4809	-	2.2939	-	0.5144	-
AD^2*	625.3888	-	685.0225	-	611.5575	-

Chapter 5

Implications in the market

The discussion in Chapter 4 identified and quantified strategic positions by the means of the models in equation (4.2), equation (4.3), and equation (4.4). While these positions mark the German balancing energy market to be actively deployed in the management of electricity portfolios, their relevance with respect to alternative marketplaces and the market design as such cannot be evaluated directly from the positions.

This Chapter[1] bridges this gap and analyzes the implications of the determined strategic positions on the day-ahead market and the capacity reserve market. In the case of the day-ahead market, the analysis is based on the combined econometric model in equation (4.3) and equation (4.4). However, the strategic positions identified in this model indicate average positions, and allow conclusions solely on a general level. Therefore, the analysis cannot be extended to a particular hour and the proposed implications represent an average interaction of the marketplaces.

The day-ahead market price is used to represent the general electricity market on from hourly to longer time frames. Specifically, it is assumed to represent the capacity reserve market and futures of longer delivery periods. On a sub-hourly time frame there are no day-ahead market contracts and the strategic positions have a similar effect as the deployment of capacity reserve. Therefore, the capacity reserve market is used as a reference point in the analysis on this time scale. In this case the discussion in Section 4.3 suggest to resort to an out-of-sample quarter-hourly pattern because a change in the general shape of the load profile can be disregarded.

[1]This chapter is based on Möller *et al.* (2009a)

5.1 Literatur review

Capacity reserve is provided by facilities that can also bring their capacity to market on the day-ahead market. This interdependence of the two marketplaces is recognized by Simoglou and Bakirtzis (2008) and analyzed by Wieschhaus and Weigt (2008) in different theoretical market settings. Wieschhaus and Weigt find that the design and the competitiveness of the capacity reserve market directly influence the prices realized in the day-ahead market and reflect the respective equilibrium between the marketplaces. Moreover, the number of market participants able to meet the prequalification standards and partake in the capacity reserve market shows to be a key factor to increase the competitiveness. In an empirical analysis of the German market Weigt and Riedel (2007) observe a correlation of positive reserve capacity prices in the capacity reserve market and day-ahead market prices and confirm the interdependence of the two marketplaces. Therefore, in the context of this analysis the day-ahead market prices represent also the capacity reserve market. However, in the concentrated German electricity market these prices might be affected by market power. (See Section 2.3)

The issue of market power in the German market is controversial. There are studies like EU (2007), von Hirschhausen *et al.* (2007), and Schwarz and Lang (2006)) that identify substantial market power abuse. However, all three studies are based on a market simulation that serves as a fully competitive reverence for the empirical prices. The criticism is focused on this market simulation. As Ockenfels (2007b) points out it is hard to distinguish the detection of market power abuse from the detection of a bias imposed by the necessary model simplifications of the simulation. The objective of the analysis in this chapter is the interplay of the balancing energy market with the day-ahead market, regardless of its price formation. Therefore, the issue of market power abuse is neglected in the subsequent analysis. However, the methodology of the market power studies is adapted and applied in a simplified form. It is used to asses the impact of strategic positions in the balancing energy market in the day-ahead market.

5.2 Marketing capacity reserve in the balancing energy market

In Section 4.3 the quarter-hourly pattern resulting from the discrepancy of the quarter-hourly settled balancing energy and a minimal delivery period of one hour in the day-ahead market was discussed. It provides an incentive for BRPs to deviate in opposite direction to the deviation indicated by the quarter-hourly pattern (i.e., receive payments during periods with an expected high net deviation and balancing energy price in the control area, and make payments during periods with low prices).

In this section a BRP able to shift part of its portfolio within an hour and obtain a negative correlation to the quarter-hourly pattern for that part is considered. Like the activation of capacity reserve bids this strategy reduces the control area's net deviation. Thus, the strategy aids network security. In this sense, the balancing energy market can be used as a market for capacity reserve. It is important to note that balancing energy prices are uncertain at the time of portfolio adjustments. Therefore, such strategic positions have no secure profits but offer statistical-arbitrage gains.

The profitability of the described strategy is analyzed in a simulation on historical data. In this simulation a strategy of shifting one MW of electricity within each hour is implemented. The energy is shifted from the two quarter-hour intervals with the highest expected net deviation and prices to the intervals with a lower expected net deviation. The expected net deviation is determined by the weekly average pattern of the preceding year (in the case of 2003 the 2004 pattern is resorted to). These patterns are calculated as the yearly average values conditional on the hour within a week. Provided the technical feasibility of shifting energy in a portfolio on a 15 to 30 minute time scale, the results in Table 5.1 demonstrate that the quarter-hourly pattern can be profitably deployed. The profitability is similar to that of marketing one MW on the capacity reserve market that Weigt and Riedel (2007) estimate to be 50,000€/a. Moreover, the profitability differs between the four German control areas. This is a consequence of a differing intensity of the quarter-hourly pattern in the control areas.

Further inspection shows that not all hours contribute equally. Naturally, the statistical-arbitrage gains concentrate in the hours with a large gradient of load, when the spread between the expected net deviations within one hour is especially pronounced. As an example, exploiting the statistical-

Table 5.1: Estimated yearly gains by shifting 1MW according to quarter-hourly pattern

Year	RWE [€/a]	e.on [€/a]	EnBW [€/a]	Vattenfall [€/a]
2003	38,098	24,815	29,835	47,362
2004	45,503	26,322	33,784	45,234
2005	34,292	24,688	28,800	55,112
2006	37,688	19,521	46,269	65,797
2007	34,517	16,597	40,359	59,183
2008	49,953	13,814	48,932	79,170

arbitrage potential between six and seven at weekday mornings contributes up to 16% to the overall gains, while it only represents 3% of time. Figure 5.1 displays the contribution of the 24 hours in a day as assessed in the simulation for the RWE control area. Evidently, the strategy is profitable in all hours. However, an implementation of the strategy in selected hours suggests itself because of the strong variation betweeen the contribution of the individual hours. The corresponding firgures of the remaining three control areas are added in Appendix E.1.

Concluding, the quarter-hourly pattern can be used to market capacity reserves. Furthermore, there are two advantages the balancing energy market compared to the capacity reserve market. First, there is no response time requirement to be met. In fact, the described strategy can be implemented already during operational planning procedures at an arbitrary time horizon. Second, the duration of alternations under the described strategy is at most half an hour. These advantages are particularly relevant in realizing the demand side management potential of facilities that cannot meet prequalification standards of the capacity reserve market. In this context the decreasing amplitude of the quarter-hourly pattern observed in Section 4.4 is an indication of market participants implementing the described strategy.

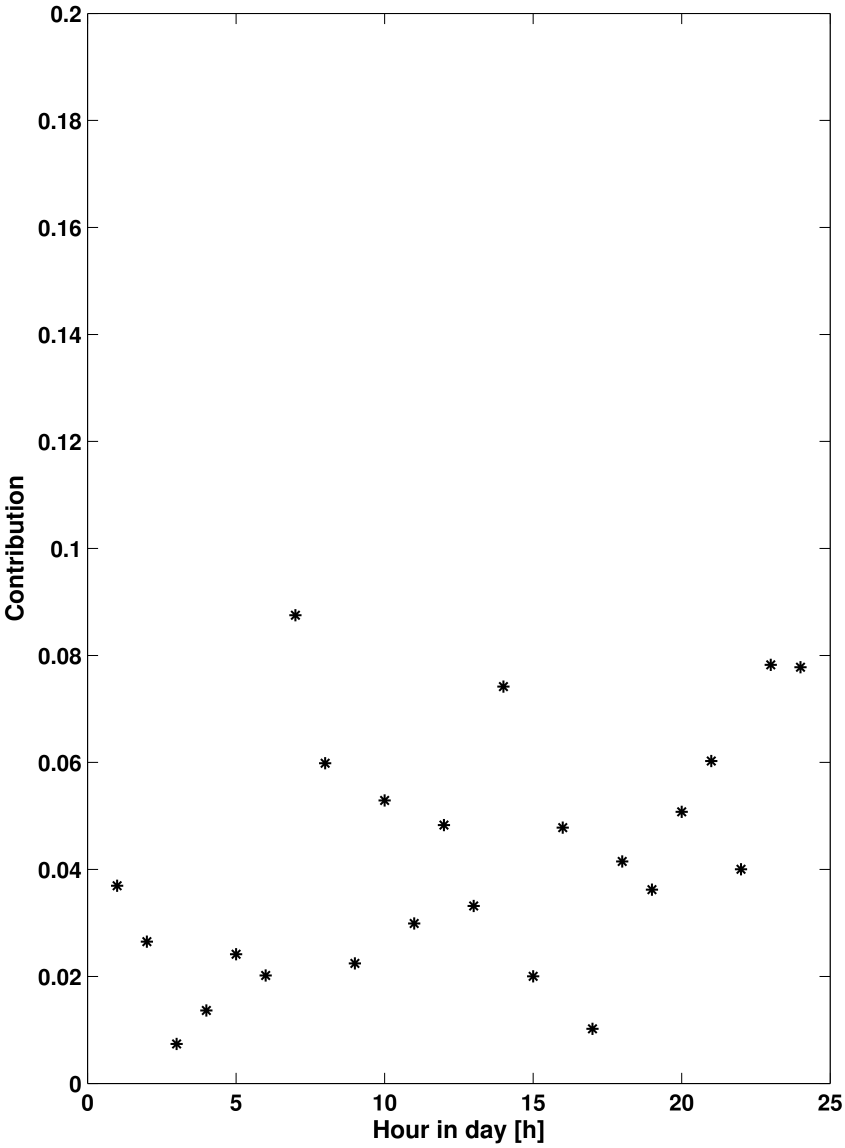
5.3 Impact on the day-ahead market

5.3.1 Balancing energy as virtual supply or demand

The quarter-hourly pattern has no interaction with futures markets because the hourly average value of this pattern is always zero. However, after integrating the balancing energy demand to hourly values predictable components remain in the data. These are the strategic positions modeled in Section 4.4 and Section 4.5. By these positions the preliminary schedule is improved with respect to the uncertainty of the electricity portfolio and the asymmetry of the balancing energy cost function. Whatever the incentives behind these positions are, the positions always coincide with a countering position in the futures market. That is market participants omit to settle part of their portfolios in the futures market and move these positions to the balancing energy market.

As an example the situation of a predictable positive net balancing energy demand is considered, when the control area is in undersupply relative to an unbiased minimum variance forecast. To resolve this situation additional electricity has to be bought in the futures market. Equivalently, a predictable negative balancing energy demand could be resolved by selling electricity. Compared to a situation with an unbiased forecast, a positive

Figure 5.1: Contribution to the quarter-hourly strategy in the RWE control area



balancing energy demand is therefore termed a virtual supply in the futures market and a negative position is termed virtual demand. Under the hypothesis of an absence of strategic balancing positions the day-ahead market settles at different prices. Positions otherwise withheld from the market will either directly or indirectly, by releasing capacity bound in other trades, be entered in the day-ahead market.

In this section the impact of the hourly pattern and the long-term pattern in the day-ahead market is assessed. In this assessment the strategic positions are provided by the forecasted values of the respective models in Chapter 4. These strategic positions represent the virtual supply and demand in the day-ahead market and are evaluated in a market simulation. For the purpose of this simulation the virtual demand and supply induced by the balancing energy positions are assigned entirely to the day-ahead market.

The simulation is based on an adaption of the day-ahead market model used in Burger *et al.* (2004). In this model hourly electricity prices are estimated by an empirical price load curve (PLC) and a grid load measurement adjusted for availability. For a detailed description of the model refer to Burger *et al.* (2004). In contrast to the original model, the model is adapted directly to the electricity prices rather than the logarithmic prices as to avoid the issue of prices at or below zero.

Yearly average PLCs are estimated from load data published by the UCTE and hourly electricity prices at the EEX. Furthermore, the load data is adjusted for availability calculated from the monthly operation of base units as published by the UCTE. For the years 2003-2005 the load values are expanded from the published incomplete UCTE data set by transferring the seasonality of the 2006 to 2008 data. Additionally, a price spike of 1500€ is set at the thermal capacity limit to account for price in scarcity situations. Figure 5.2 shows the estimated PLCs for the years 2003-2008.

Using these PLCs an equivalent load time series is extracted from the data also representing the short-term market situation. This equivalent load is used as a base scenario to simulate the market prices without the strategic balancing energy positions identified in Chapter 4. The results are displayed in Table 5.2. It is important to note that the balancing energy position has to be scaled to relate it to the adjusted load. This scaling factor is determined by the demand fraction of 15% actually traded in the day-ahead market. (See Michalk (2008).) So on average the balancing energy positions have to be scaled up by a factor of 6.7 to correspond to the load values the model is calibrated on.

The most dominant effect of the hourly pattern is reducing demand in peak hours and increasing demand in off-peak hours. Consequently, the

Figure 5.2: Estimated price load curves

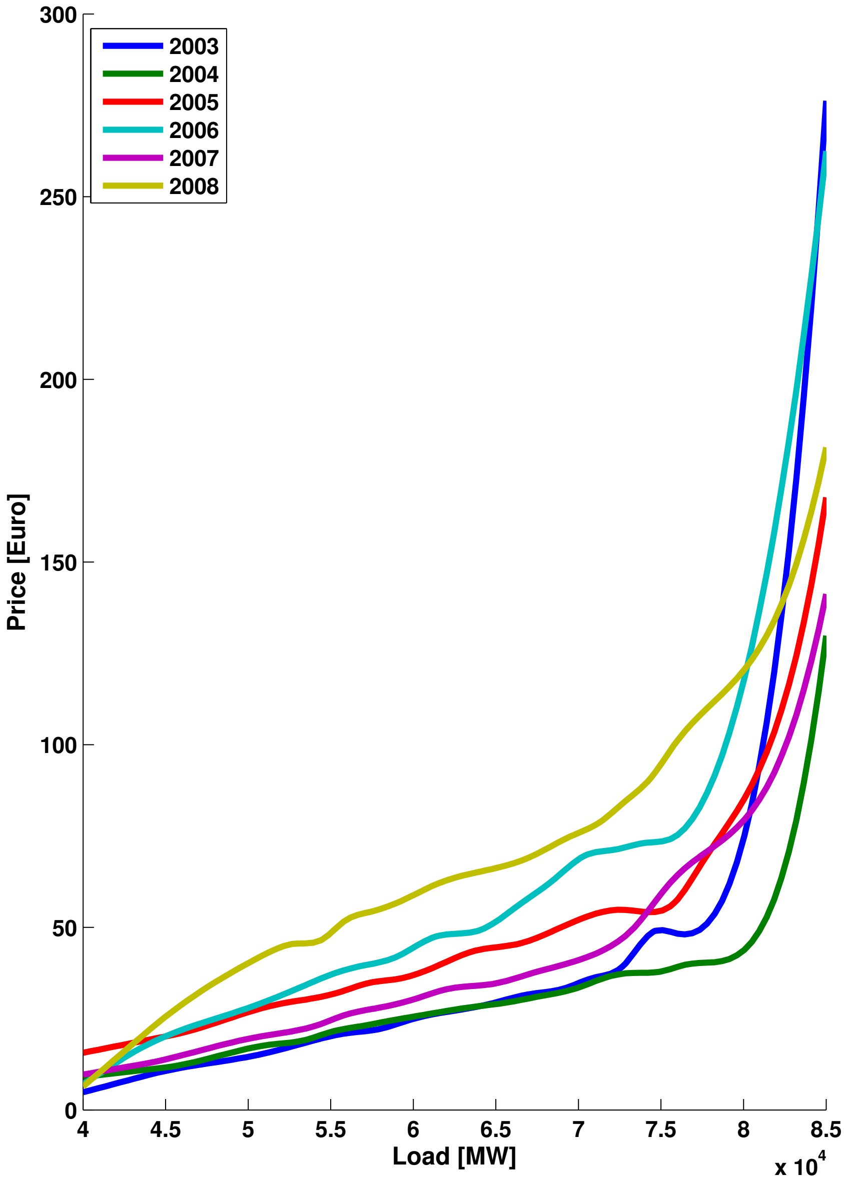


Table 5.2: Estimated price mark-up induced by strategic balancing energy deployment

	Hourly pattern			Long-term	Σ_{tot}
Year	Off-peak	Peak	Σ_h		
2003	0.0134	-0.0694	-0.0278	0.1291	0.1107
2004	0.0299	-0.0075	0.0125	0.0589	0.0692
2005	0.0192	-0.0322	-0.0045	0.0597	0.0294
2006	0.0269	-0.0296	-0.0008	-0.0050	-0.0087
2007	0.0084	-0.1171	-0.0538	0.0900	0.0267
2008	0.0366	-0.0825	-0.0191	0.0574	0.0258

price volatility is dampened. Furthermore, a price reducing effect of this pattern in total can be observed. This is a consequence of the increasing slope of the PLC at high loads resulting in a stronger impact of the hourly pattern during high load peak hours. Here, the year 2004 stands out with a positive total. This simple simulation does not allow analyzing this in detail, but it should be noted that there are more off-peak than peak hours and the estimated PLC is comparatively flat in 2004. This PLC reflects the absence of electricity price spikes in the day-ahead market in 2004 and could explain the determined net price increasing effect in 2004.

The long-term deployment of balancing energy influences prices as well. Moreover, these strategic positions continuously influence the day-ahead market in the same direction. Consequently, this effect dominates the total price impact of balancing energy in the analysis. In view of the detected long-term balancing positions the findings correspond to the average long-term positions in Table 4.6. In terms of the total impact the year 2003 shows to have the highest mark-up estimation in the sample. It indicates about 11% of the electricity price to be due to virtual demand induced by long-term balancing energy positions. This mark-up decreases gradually until it practically vanishes in 2006. The last two years show moderate average mark-ups.

Due to the necessary simplifications the model can only provide an order of magnitude of the impact of balancing energy deployment. An in-depth simulation including availability and market share information on an hourly basis would be essential to obtain quantitative sound results. Nonetheless, the results indicate that the balancing energy market not only serves as an alternative marketplace to the day-ahead market but also directly influences the day-ahead market.

Also, another investigation of the German day-ahead market confirmes the identified impact of strategic balancing energy positions in the day-ahead market. A brief study of EEX order book data revealed that a change in demand by as little as 135 MW could trigger a price increase of 23% or over 500€/MWh in a spike regime. (See Ehlers *et al.* (2007).) These findings underline the relevance of positions in the order of hundreds of MW —such as the virtual supply and demand induced by strategic balancing energy positions— in the day-ahead market. It also gives a direct example of the detected hourly pattern being able to reduce spike risk. Moreover, this strong influence of relatively small changes in demand underlines the need to amplify the assessed balancing energy demand when used in our market simulation that is adapted to total grid-load.

5.3.2 Balancing energy and market power

The investigation of the impact of balancing energy positions in the day-ahead market reveals significant price alterations imposed by the long-term deployment. These long-term positions show particularly high levels of oversupplied control areas from 2003 to 2005 as indicated by the results in Table 4.6 and Table 5.2. The same period of time is also covered in three studies of market power. (See EU (2007), von Hirschhausen *et al.* (2007), and Schwarz and Lang (2006).) It suggests itself to analyze the possible error imposed by neclecting the balancing market because none of these studies take into account its influence on day-ahead market prices.

All studies apply a similar methodology: hourly market prices are compared to model prices derived from models based on fundamental market data. The data base described in the studies on the other hand differs. Especially, one study relies on a strong data base being provided with confidential company background by the EU commission. (See EU (2007).)

The general criticism of the methodology of all studies focuses on systematic errors imposed by the inherent model simplifications. One such example is neglecting scarcity pricing near the capacity boundary as done in all the analyses discussed. Obviously, under this simplification the model price will be lower even when compared to a perfectly competitive market price. This example suffices in this context, refer to Harvey and Hogan (2002), Ockenfels (2007a), and Swider *et al.* (2007) for a detailed analysis of systematic errors. However, it might illustrate how difficult a quantitative interpretation of results is. As Newbery *et al.* (2004) state it is plausible that the influence of systematic errors is constant over time within one specific country and modeling approach. In other words, while the absolute values are difficult to interpret and difficult to compare among the studies, the evolution of detected levels can be interpreted as long as relevant boundary conditions are constant.

Following this interpretation Table 5.3 presents the results of the three studies. They are presented jointly using the price cost mark-up (PCMU). In addition, an indicator summarizing the overall indication of the studies is provided. The results of all studies are compatible within the same year.

Table 5.3: Results of market power studies by comparison taken from Schwarz and Lang (2006), von Hirschhausen *et al.* (2007) and EU (2007)

Year	$PCMU_{S\&L}$	$PCMU_{vH}$	$PCMU_{LE}$	
2000	-0.06	-	-	o
2001	-0.09	-	-	o
2002	0.04	-	-	o
2003	0.40	-	0.59	++
2004	0.22	0.19	0.22	+
2005	0.15	0.14	0.15	+
2006	-	0.25*	-	+

One should, however, appreciate that the studies relay on a similar methodological approach. This holds especially for the studies von Hirschhausen *et al.* (2007) and Schwarz and Lang (2006). The studies indicate the highest mark-up in 2003. Furthermore, the magnitude of the mark-up decreases from 2003 to 2005. The 2006 value is listed for the sake of completeness. However, the methodology and data source was changed in the corresponding analysis. Consequently, the assumption of constant boundary conditions is questionable for this value.

When compared to the average long-term balancing energy deployment in Table 4.6 a similar evolution is evident. In 2003 the control areas are in strong oversupply. This level of oversupply then diminishes in the following two years. As demonstrated in Section 5.3 the change in virtual demand in the day-ahead market effects electricity prices during this period of time in much the same way. The methodology of all three studies neglects the balancing energy market. It therefore constitutes a systematic error that is not considered in previous evaluations. In view of the systematically oversupplied control areas during the analyzed time period, all three studies show to be sensitive to this error.

In contrast to other systematic errors, the error of neglecting the influence of the balancing energy market could be interpreted as a sensitivity analysis of market power measurements. In such an approach an analysis including demand induced by the balancing market would represent market power abuse, while the exclusion would represent an unbiased market. In fact, von Hirschhausen *et al.* (2007) test their analysis in a similar way.

In their work they approximate the level of additional demand required to explain their results in a perfectly competitive market environment. As an example, a constant additional demand of 9 GW is estimated for the year 2004. For the same year the average long-term induced demand explains 30% of this additional demand. In the context of this analysis these studies of market power support the assessed impact of balancing energy positions in the day-ahead market. This impact indicates that the strategic positions in the balancing energy market are not only influenced by the day-ahead market prices but in turn also influence the day-ahead market prices.

Chapter 6

Summary and conclusion

6.1 Summary

This thesis discusses the deployment of balancing energy in the management of electricity portfolios in the particular setting of the German electricity market. In contrast to other European electricity markets the German market design encourages active positions in the balancing energy market within certain limits. Consequently, the balancing energy demand shows predictable components in addition to the fluctuations imposed by unforeseen events. In this analysis these components are decomposed into three positions that are well characterized by the time frame of their deployment. Namely these positions are quarter-hourly, hourly and long-term positions. At the same time this decomposition allows a separation of the balancing energy market's interplay with the capacity reserve market and the interplay with the general market represented by the day-ahead market. In the following the main findings of this analysis are summarized.

6.1.1 Quarter-hourly pattern

Within the hour different settlement periods in the day-ahead and balancing energy market lead to a pronounced quarter-hourly pattern as discussed in Section 4.3. A high spread between balancing energy prices during up- and down-regulation periods translates into an economical incentive to reduce the correlation of an electricity portfolio to this quarter-hourly pattern. This strategy reduces load fluctuations in the network, which is equivalent to the deployment of capacity reserve. The quarter-hourly pattern can only interact with the capacity reserve market because the hourly contracts in the day-ahead market inhibit an interaction with the futures market on the sub-hourly time frame. On the quarter-hourly time frame a corresponding strategy sets capacity reserve free otherwise deployed to compensate fluctuations.

The quarter-hourly pattern is attributed to gradient of load within individual hours that cannot be reproduced by the hourly contracts in the day-ahead market. Overall it can be said that the production side of the market follows the step function schedule indicated by hourly day-ahead contracts while the consumption changes gradually. This discrepancy results in the quarter-hourly pattern and it can therefore be modeled by the gradient of load as in equation (4.2). However, the pattern shows to be very persistent over the years and a higher accuracy of modeling can be obtained by the out-of-sample average pattern of the preceding year. Therefore, it suggests itself to model the quarter-hourly pattern by this factor, unless a change in the general shape of the load profile is expected. In addition, the amplitude of the quarter-hourly pattern diminishes over the analyzed period. This indicates an implementation of the corresponding strategies in the management of electricity portfolios.

6.1.2 Hourly pattern

On an hourly time frame a pattern resembling the German load profile is identified in Section 4.4. However, the amplitude of this pattern varies between the years analyzed. This variation is linked to changes in the statistical-arbitrage incentive between the balancing energy market and the day-ahead market. Therefore, the hourly pattern shows that market participants exploit statistical-arbitrage opportunities. In other words, the hourly pattern can be understood as the exercise of grid-access as a real option in many ways comparable to a swing option. Only through the hourly pattern may the electricity price in the day-ahead market and the balancing energy market reach equilibrium, and a preliminary schedule reflecting the inevitable uncertainty of the electricity load is achieved.

The hourly pattern shows saturation at high statistical-arbitrage incentives that reflects limits for strategic positions in the balancing energy market. It is modeled by a two factor model with three parameters. (See equation (4.3).) In this model the first factor captures the varying statistical-arbitrage incentive. The second factor incorporates technical peculiarities that remain constant over time. In comparison to an in-sample fit of the average hourly-pattern this model reaches similar R^2 values with resorting to in-sample information.

6.1.3 Long-term pattern

The residuals of the hourly model show strong autocorrelation. Therefore the hourly model is supplemented by a SARIMA-model in Section 4.5.1. This SARIMA model in Table 4.5 constitutes a linear correction to the predictions of the hourly pattern. Moreover, it identifies positions taken in the balancing energy market over extended periods of time that cannot be captured by the hourly model. Changes in these long-term positions coincide with changes in the asymmetric cost function of balancing energy. This observed asymmetry provides an economic incentive to present a trimmed preliminary schedule in order to reduce deviation cost. Historically, the asymmetry displays a tendency to drive the market towards oversupply.

In addition, the distribution of the innovations is analyzed in detail. The distribution of the innovations exhibits strong heavy-tailedness that reflects the bearing of extreme events on the balancing energy demand. At the same time, balancing energy demand is constrained by physical boundary conditions that restrict events in the fare-tails. These characteristics are uniquely captured by the CTS-distribution that is proposed for the innovations, while the t-distribution and the α-stable distribution are rejected at the 5% significance level.

The long-term model can only be used in combination with the hourly model because it is adapted to its residuals. Furthermore, by incorporating the dynamics of the two factors in the hourly model the residuals can be modeled with one SARIMA model over the entire analyzed time frame. Therefore, the combination of hourly factor model and the SARIMA-model can be employed to calculate hourly expectation values conditional on the hour within the week and a given day-ahead market price. Additionally, the proposed CTS-distributed innovation process allows an assessment of the associated risk.

6.1.4 Interplay with the capacity reserve market

The discussion in Section 4.3 establishes the quarter-hourly pattern that prevails as no other liquid marketplace exists outside the balancing energy market. Nonetheless, the diminishing amplitude of the quarter-hourly pattern indicates its active deployment in the management of electricity portfolios. Such a strategy is equivalent to the deployment of capacity reserve and its profitability is analyzed in a backtest in Section 5.2.

Based on the prediction of the out-of-sample quarter-hourly pattern of the preceding year one MW of electrical power is shifted in all hours to reduce the correlation of an electricity portfolio to the pattern. Therefore, the strategy is neutral with respect to energy transactions over hourly periods.

In a backtest this strategy is on average profitable in all hours in all four control areas. However, the gains are concentrated in the hours with a steep gradient of load when the quarter-hourly pattern in most pronounced. This suggests the implementation of the strategy in the most profitable fraction of hours.

Overall, the strategy results in earnings similar to those in the tertiary capacity reserve market. In contrast to the capacity reserve market the earnings are generated entirely by energy payments instead of capacity payments that dominate earnings of tertiary capacity reserve. Moreover, there are no pre-qualification standards that have to be met. In particular, the strategy can be employed at arbitrary response time. Consequently, the strategy potentially attracts additional capacity reserve into the market that cannot be brought to the market in the capacity reserve market. Notwithstanding, the detected amplitude and profitability of the quarter-hourly pattern allow for a further implementation of corresponding strategies.

6.1.5 Interplay with the day-ahead market

The day-ahead market price has a strong bearing on the balancing energy demand on an hourly and longer time frame. This dependence is reversed in Section 5.3 that analyzes the impact of strategic balancing energy positions in the day-ahead market. The analysis is based on a simple market simulation using the historic market prices as a reference price. From this reference scenario the price changes imposed by the hourly and long-term pattern are estimated.

Both patterns are able to influence the prices in the day-ahead market. In the case of the hourly pattern the analysis shows only a minor impact on the average price of electricity. Prices are reduced by imposed virtual supply in the peak hours and increased by virtual demand during off-peak hours, resulting in a dampening of volatility. In the case of the long-term pattern the balancing energy market's tendency towards oversupply creates a virtual demand that increases prices in the day-ahead market. In the same years the long-term pattern creates pronounced virtual demand, relevant studies of market power in the German electricity market identify high mark-ups. In the context of these studies neglecting the effect of long-term balancing energy positions constitutes a systematic error. Therefore, the studies support the assessed influence of strategic balancing energy demand on day-ahead market prices further.

6.2 Conclusion

The identified three predictable patterns in the German balancing energy demand are clearly incompatible with a minimum-variance forecasting objective of all market participants. Also anohter statistical forecasting objective, such as minimal absolute error or maximum likelihood, is implausible in view of the proposed distribution of the innovations. This distribution slight asymmetry cannot explain the positions determined in the analysis by the deviation of the mean and median value and the mean and modal value, respectively. In contrast to the dual-price settlement scheme the single price settlement scheme of the German electricity market therefore does not advocate a forecasting objective in statistical terms. Instead, the market seems to follow a best economical forecast objective. Part of the electricity portfolio is actively allocated in the balancing energy market whenever its expected price is competitive. This interpretation is further supported by the dynamic changes in the positions. These changes make simple reluctance of market participants to employ adequate forecasting procedures implausible. Moreover, these changes are linked to statistical-arbitrage incentives between the balancing energy market and alternative marketplaces.

In general, these incentives exist in the dual-price settlement scheme adopted in other European countries as well. However, the imposed transaction cost and penalties inhibit their exploitation by market participants. In the case of the quarter-hourly pattern the balancing energy market adds a liquid and transparent marketplace to trade electricity on a sub-hourly time frame. The implementation of this pattern in the management of electricity portfolios results in a similar interaction as the deployment of capacity reserve. In contrast to the capacity reserve market no prequalification standards apply. This is especially advantageous to the demand side management (DSM) capacity that cannot meet the technical requirements such as response-time and availability requirements and set by the TSO. As a result additional flexible capacity enters the market. This tapping of network stabilizing capacity can contribute to the preparation of the electricity market for an increased share of renewable electricity sources. In contrast, a dual-price system will even undermine system security with respect to the quarter-hourly pattern. The imposed transaction cost drive also BRPs negatively correlated to the net deviation to reduce their fluctuations. Consequently, the net deviation will increase because the stabelizing countering fluctuations are reduced.

The hourly and long-term patterns lead to a growth of load fluctuations potentially destabilizing the network. However, these positions are in line with the price signals set by the market. Moreover, the price dampening effect of the hourly positions effectively reduces the ability to exploit market power in scarcity situations of electricity supply or demand. Overall the hourly pattern reflects a reduction of the total cost of electricity supply under demand uncertainty. Also the long-term positions tending towards negative balancing energy demand help to reduce the cost of inevitable fluctuations because the more expensive regime of positive balancing energy demand is avoided. The combination of hourly and long-term pattern therefore drives the market towards an optimal starting point for balancing also reflecting that up-ward regulation is more demanding than down-ward regulation.

In view of a potentially destabilizing effect it should be added that there is no indication that the German system's stability was inferior to that of neighboring markets with a dual-price settlement scheme. In fact, the market design strongly discourages extreme positions in the balancing energy market because statistical-arbitrage returns can be realized with a deviation opposing the net deviation of the control area. Therefore, any strategic position dominating the market will be misguided and highly unprofitable speculation. In addition, a dual-price settlement scheme is only effective in undermining the hourly pattern. It may well result in long-term biased forecasts as the examples of England and Poland demonstrate. In these cases the strategic positions do not only reflect the asymmetric cost of positive and negative balancing, but also reflect the distortions inflicted by the imposed transaction cost. However, these positions have a direct impact on electricity prices in the day-ahead market. In view of this impact TSOs should not only be bound to a secure grid operation and network stability, but also take an active role in ensuring representative market prices in the day-ahead market. This is especially true because the distortion of prices imposed by long-term balancing energy positions is identified as market power abuse by relevant studies.

The model outlined in this thesis is implemented to forecast balancing energy demand conditional on the time and the electricity price in the day-ahead market. Moreover, the proposed CTS-distribution is able to capture the combination of highly relevant extreme events and limiting physical boundary conditions that characterize the unpredictable components of balancing energy demand. Therefore, this model can be employed to increase the precision of capacity procurement with respect to a given security level of the electricity system. In this, largest possible event considerations would be supplemented by conditional probabilities of safety for a given procurement. On the side of market participants the model provides a basis for the implementation of the discussed strategies. However, the model has to be expanded so that implicit trading cost such as the market impact can be evaluated. Furthermore, this expansion would allow transferring the model to a market with a dual-price settlement scheme and its transaction cost and penalties.

Overall, the experience of the German balancing energy market demonstrates that the market responds to the incentives set by the market design, and indicates balancing energy to be an integral component of electricity portfolio management. This constitutes a major conceptual difference to a dual-price settlement scheme that is designed to inhibit any interaction of the balancing energy market with alternative marketplaces. Through this interaction an economical optimal starting point for network operation can be mediated, so that the cost of electricity under uncertainty is reflected. Furthermore, an additional reduction of load fluctuations is made accessible by separating the resolving of a biased forecast from its originator. One such example is the quarter-hourly pattern where the originator might not have the technical means of resolving the known forecasting error. Moreover, under the dual-price scheme small portfolios are laden with higher penalty cost because the effect of netting fluctuations is reduced. Therefore, the single-price scheme does not discriminate against BRPs with small portfolios as does the dual-price settlement scheme. In total the single-price balancing energy market helps to direct investment into the most economical alternative between capacity extensions and more advanced forecasting procedures to secure system security. These are key issues in adapting the electricity market for the challenges of integrating a higher share of renewables. With respect to a further harmonization of the European electricity markets the described advantages have to be weighed against the traditional security considerations that are dominant in other European markets.

6.3 Outlook

Throughout this thesis balancing energy prices are not directly addressed despite their obvious importance. The reason behind this simplification is that there is no German balancing energy price corresponding to the single German wholesale market. Thus, the prices can only be analyzed in a given control area. However, demand is the key price setting factor for balancing energy. Therefore, the model for balancing energy demand could be combined with a model for balancing energy prices conditional on demand to create a price model for the respective control areas. After the period analyzed in this thesis, three of the control areas combined their settlement of balancing energy. Starting from April 2009 all control areas but the RWE control area display a common net deviation and balancing energy price. The RWE control area is scheduled to join this scheme by June 2010. Therefore, a direct analysis of balancing energy prices suggests itself for future research.

There was an additional change in the price formation of balancing energy after the analyzed period. Negative prices were introduced in January 2009 with the exception of the Vattenfall control area that followed one month later. In fact, corresponding transitions had taken place in the intra-day and day-ahead market in September 2007 and September 2008, respectively. This late transition resulted in arbitrage opportunities in late December 2008 when negative prices first accured in the day-ahead market. In contrast to the statistical-arbitrage opportunities discussed in this thesis, these opportunities were profitable regardless of the control area's net deviation and thereby potentially endangering network security. While this situation was resolved by the introduction of negative prices in the control areas the negative prices might have a lasting impact on the asymmetry of the balancing energy cost function. In turn this should influence the long-term positions taken in the balancing energy market, which outlines another direction for future research.

Part III

Appendix

Appendix A

Measures of market concentration

Market concentration is a controversial issue in electricity markets. The short term inelastic demand paired with a the steep increase of the merit-order curve at peaking units potentially allow market participants with large generation capacity to exploit their market power by withholding part of their capacity. Therefore, different measures are used to monitor the level of market concentration and detect a possible abuse of market power. The discussion in this section is based on the discussion in EU (2007) that also provides one of the relevant studies referenced in Section 5.3.2.

A.1 Concentration ratio

The concentration ratio (CR(n)) measures the joined market share (s) of the largest n players and is calculated as follows:

$$CR(n) = \sum_{i=1}^{n} s_{(i)}$$

In the case of the German electricity market the CR(4) is almost 90% in terms of generation capacity suggesting an oligopoly. In terms of retail sales the CR(4) is about 50% suggesting a higher degree of competition. However, the CR(n) value does not indicate the concentration among the n largest players nor does it reflect if the players are able to exploit their dominant position. In particular, the measure CR(n) does not reflect the high dynamics of hourly changing electricity demand. Therefore, the concentration ratio is of limited validity concerning the competitiveness of electricity markets.

A.2 Herfindahl-Hirschman index

Like the concentration ratio the Herfindahl-Hirschman index (HHI) is based on the market share (s) of the individual players measured in percent. However, the information of all players (N) is considered in its calculation. The HHI is calculated based on percent values:

$$HHI = \sum_{i=1}^{N} s_i^2$$

Therefore, the HHI ranges from $10,000 \cdot \frac{1}{N}$ in a perfectly competitive market to $10,000$ under a monopoly. A market is said to be concentrated at HHI values above $1,800$. However, in the case of energy markets a threshold value of $2,500$ is suggested by regulators. In the case of the German market a average HHI-value of $1,914$ is calculated indicating a market on the borderline to concentration. As in the case of the concentration ratio, the HHI does not reflect the actual ability of players to exploit their position in the market, and can therefore indicate only the concentration but does not directly address the level of competition in the market.

A.3 Pivotal supplier index

To resolve the shortcomings of the CR(n) and the HHI electricity market specific measures are proposed. The pivotal supplier index (PSI) is a binary indicator. Its value is one if the capacity controlled by a given company (C_C) is indispensable to supply the electricity demand (D) in an hour and zero otherwise. Thus, the percentage of all hours (H) a company is pivotal gives an indication weather the company could exercise market power.

$$PSI_C(\%) = \frac{\sum_{i=1}^{H} \mathbb{1}_{(-\infty,0)}(D - C_C)}{H}$$

A threshold value of 20% is suggested to identify markets that are not competitive. For the German market only the largest player has an average PSI of 49% that is above the threshold value.

A.4 Residual supply index

The binary variable PSI cannot capture the varying degree to which a company might be pivotal in a market. Therefore, the concept is generalized in the residual supply index (RSI). Its value gives the total available capacity (C_{tot}) not controlled by a given company in percentage of the electricity demand in an hour.

$$RSI = \frac{C_{tot} - C_C}{D}$$

It is suggested that a market might not be competitive if the RSI exceeds 110% in over 5% of the time. For the German market two companies pass that threshold with an exceedance in 77% and 48% of the time, respectively.

A.5 Lerner index

All measures discussed in the previous sections are focused on the potential exercise of market power but give no indication of an actual abuse of market power. The Lerner index (LI) captures this information in the percentage of market prices (P) explained by a lack of competition. In its calculation the price of the perfectly competitive market is assumed to be the marginal cost (MC).

$$LI = \frac{P - MC}{P}$$

Hour specific marginal cost are problematic to obtain in electricity markets. They have to be inferred from a market simulation that in turn relies on model assumptions and simplifications. A detailed discussion of this issue can be found in Ockenfels (2007a; 2007b) and Möst and Genoese (2009).

A.6 Price cost mark-up

In essence the price cost mark-up (PCMU) is just an alternative expression of the information in the LI. However, it uses the marginal cost as the point of reference. Therefore, the PCMU presents the mark-up the market players are able to add due to lack of competition.

$$PCMU = \frac{P - MC}{MC}$$

Again, the marginal cost are the crucial factor and their estimation is controversial.

Appendix B

Network access contracts

Despite encouraging strategic position in the balancing energy market in the market design, the German TSOs also acknowledge the potentially adverse effect of strategic positions on system security. This view is reflected in the grid-access contracts that bind BRPs with the TSO in the respective control areas. In this chapter three sample contracts are analyzed with respect to their implication on the forecasting procedures of the BRPs concerned. (See Bundes Netz Agentur (2006), Vattenfall Europe Transmission (2009b) and E.ON Netz (2008).) The analysis is strictly aimed at the statistical aspects of these sample contracts while judical aspects are excluded.

All sample contracts impose limits on the level of the strategic deployment of the three patterns proffered in this thesis. The following sections quotes relevant passages of the three sample grid-access contracts in German and their suggested translation into English.

B.1 Excerpt from Bundes Netz Agentur

"... Die Inanspruchnahme von Ausgleichsenergie zur Lastdeckung bzw. zur Kompensation einer Überspeisung des Bilanzkreises ist nur zulässig, soweit damit nicht prognostizierbare Abweichungen ausgeglichen werden. Sofern der BKV nicht alle zumutbaren Anstrengungen unternommen hat, prognostizierbare Abweichungen zu vermeiden, stellt dies grundsätzlich eine missbräuchliche Inanspruchnahme von Ausgleichsenergie dar. ..."

"... Die ... erstellten Fahrpläne müssen vollständig sein und eine ausgeglichene Viertelstunden-Leistungsbilanz des Bilanzkreises aufweisen. ..."

"... Eine missbräuchliche Inanspruchnahme von Ausgleichsenergie liegt insbesondere dann vor, wenn ..."

- "... Regelmäßige deutliche Über- bzw. Unterspeisung Eine regelmäßige deutliche Über- oder Unterspeisung eines Bilanzkreises liegt dann vor, wenn der arithmetische Mittelwert aller negativen und positiven Viertelstunden-Abweichungen im Abrechnungszeitraum in deutlichem Maße positiv oder negativ ist oder keine ausreichende Anzahl von Nulldurchgängen vorliegt. ..."

- "... Auffällige Unterspeisung zu Zeiten hoher Börsenpreise bzw. Überspeisung zu Zeiten niedriger Börsenpreise ..."

- "... Deutliche, einseitige finanzielle Optimierung der Bilanzkreissalden (Gutschriften >> Rechnungen) im Laufe eines Jahres ..."

- "... Keine ausgeglichene Viertelstunden-Leistungsbilanz bei Bilanzkreisen, die ausschließlich Fahrplangeschäfte abwickeln. ..."

"... Für jede betroffene Viertelstunde (wird) folgende Vertragsstrafe zum Ansatz gebracht. Bei Überspeisungen werden die zur Auszahlung an den BKV errechneten Beträge einbehalten. Bei Unterspeisungen wird dem BKV zusätzlich der doppelte EEX-Börsenpreis (MCP-Preis der jeweiligen Viertelstunde) in Rechnung gestellt. ..."

"... Eine fristlose Kündigung dieses Vertrages ist zulässig, wenn ... (die) Summe der Einspeisungen von der Summe der Entnahmen ... (entweder) um mehr als 20 % über einen Zeitraum von einer Woche oder um mehr als 50 % über einen Zeitraum von zwei Tagen ..."

The contract restricts the deployment of balancing energy strictly to the compensation of imbalances caused by unpredictable events. Specifically, the BRP is required to apply all reasonable forecasting measures to provide a balanced quarter-hourly forecast of its feed-ins and withdrawals. Nonobservance of this requirement constitutes an abuse of balancing energy and will be penalized. The abuse of balancing energy is described more precisely as

- a frequent clear under- or oversupplied forecast of the BRP is identified. The forecast is clearly biased when its average value is notably positive or negative or the forecasting error does not display an adequate number of zero crossings.

- a conspicuous undersupply during times of high day-ahead market prices and oversupply during times of low day-ahead market prices respectively.

- a clear tendency to financially optimized imbalances. The money received from the TSO exceeds by far the money paid to the TSO during a one year period.

- any imbalances provided by a BRP managing a portfolio of strictly day-ahead market contracts.

Should an abuse be detected the penalties are the withholding of compensation during periods the BRP was in oversupply and a fee of twice the respective day-ahead market price on top of the balancing energy price during periods the BRP was in undersupply. Moreover, the contract may be terminated without notice if the bias exceeds 20% over a period of one week or 50% during a period of two days.

B.2 Excerpt from E.ON Netz

"... Der BKV ist verantwortlich für eine ausgeglichene Bilanz zwischen Einspeisungen und Entnahmen in jeder Viertelstunde. ..."

Die Inanspruchnahme von Ausgleichsenergie zur Lastdeckung bzw. die Überspeisung des Bilanzkreises für nicht durch stochastische Schwankungen bedingte Unausgeglichenheiten stellen grundsätzlich einen Verstoß gegen die Rechte und Pflichten aus diesem Vertrag dar. In Fällen in denen eine missbräuchliche Über- oder Unterspeisung von Bilanzkreisen im Sinne der Festlegungen der Regulierungsbehörde (Section B.1) ... vorliegt, informiert der ÜNB den BKV, fordert ihn letztmalig zur Unterlassung der Vertragsverletzung auf und weist auf die Rechtsfolgen ... hin. ... "

"... Im Übrigen kann dieser Vertrag nur aus wichtigem Grund fristlos gekündigt werden. Ein wichtiger Grund liegt vor, wenn ein Vertragspartner eine wesentliche Verpflichtung aus diesem Vertrag verletzt hat. Dies ist insbesondere bei ... wiederholter missbräuchlicher Über- bzw. Unterspeisung im Sinne (Section B.1)) der Fall. Soweit möglich und für den ÜNB zumutbar, wird der BKV vor Ausspruch der fristlosen Kündigung abgemahnt bzw. erhält die Möglichkeit die Vertragsverletzung bzw. deren Folgen zu beseitigen. ..."

This contract requires the BRP to provide a quarter-hourly balanced forecast of its feed-ins and withdrawals. Any systematic deployment of balancing energy not caused by unpredictable events is classified as abuse. With respect to sanctions and a more precise definition of abuse the contract refers to the regulator, who is the author of the sample contract in Section B.1. Moreover, the contract may be terminated without notice if an abuse of balancing energy deployment is detected repeatedly.

B.3 Excerpt from Vattenfall Europe Transmission

"... Der BKV ist insbesondere für eine ausgeglichene Viertelstunden-Leistungsbilanz der seinem Bilanzkreis zugeordneten Einspeisungen und Entnahmen

... verantwortlich. ..."

"... Der BKV ist verpflichtet, durch zumutbare Maßnahmen, insbesondere durch entsprechende Sorgfalt bei der Erstellung der Prognosen, die Bilanzabweichungen möglichst gering zu halten. Die Inanspruchnahme von Ausgleichsenergie zur Lastdeckung bzw. zur Kompensation einer Überspeisung des Bilanzkreises ist nur zulässig, soweit damit nicht prognostizierbare Abweichungen ausgeglichen werden. Sofern der BKV nicht alle zumutbaren Anstrengungen unternommen hat, prognostizierbare Abweichungen zu vermeiden, stellt dies grundsätzlich eine unzulässige Inanspruchnahme von Ausgleichsenergie dar. ..."

"... Fahrpläne müssen vollständig sein und eine ausgeglichene Viertelstunden-Leistungsbilanz des Bilanzkreises aufweisen. ..."

"... Eine fristlose Kündigung dieses Vertrages ist zulässig, bei ... einer wiederholt festgestellten und der Bundesnetzagentur gemeldeten Prognosepflichtverletzungen. ..."

As in the other sample contracts, the contract binds the BRP to provide a balanced quarter-hourly forecast resorting to adequate forecasting procedures. Specifically the contract identifies any forecast that leaves open predictable positions in the balancing energy market as abuse. A repeated detection of abuse may further be sanctioned by a termination of the contract without notice.

B.4 Discussion

In the context of the strategic position proffered in this thesis the excerpts of grid-access contracts provided in the previous sections are important because they impose limits on the extent the relevant strategies may be employed in the management of electricity portfolios. In this discussion the sample contract of the Bundes Netz Agentur (2006) takes a central position because it includes specific reference to the quarter-hourly, hourly and long-term pattern. All contracts require the BRP to provide a balanced forecast on a quarter-hourly time frame. However, this requirement cannot be interpreted as an unbiased forecast. On the contrary, the requirement calls the BRP to present a biased forecast so that it may be balanced by corresponding positions in the futures and the day-ahead market that do not offer quarter-hourly periods. Also the hourly and long-term pattern are directly addressed as potential abuse in Bundes Netz Agentur (2006). At the same time the contract leaves a bandwidth within which corresponding strategies can be executed. Namely, the strategies are not categorized as abuse up to the unspecified a threshold where they become obvious and conspicuous.

In statistical terms all contracts specify rather fuzzy limits on strategic balancing energy positions because no contract specifies a forecasting objective. Therefore, any forecast that is within the bulk of the density function of the forecast can be considered a balanced forecast in the context of these contracts. Furthermore, with respect to the patterns that are observable over the entire analyzed period and described in this thesis, it can be assumed that the forecast's mean deviation is not "clearly" positive or negative nor does it show "conspicuously" arbitrage-like correlation with day-ahead exchange prices, if justifiable within the forecast's density function.

However, the grid access contracts represent a considerable risk for a BRP should its strategic positions in the balancing energy market be classified as abuse. Nonetheless, in combination with the results presented in this thesis one can conclude that strategic positions in the balancing energy market are encouraged up to a level where they become conspicuous and excessive (i.e., a BRP has some flexibility in providing a balanced forecast).

Appendix C

Examples of math and methods

C.1 Stationarity, causality and invertibility

The following linear filter is *stationary* (see Brockwell and Davis (2002)):

$$x_t = \sum_{i=-\infty}^{\infty} \theta_i \epsilon_{t-i} \ , where \ \sum_{i=-\infty}^{\infty} |\theta_i| < \infty$$

Moreover, it is *causal* if all parameters of future innovations are zero (see Brockwell and Davis (2002)):

$$x_t = \sum_{i=0}^{\infty} \theta_i \epsilon_{t-i} \ , where \ \sum_{i=0}^{\infty} |\theta_i| < \infty$$

Therefore, the Wold decomposition theorem provides a causal representation of a stationary process.

A linar filter is *invertable* if (see Brockwell and Davis (2002)):

$$\epsilon_t = \sum_{i=0}^{\infty} \phi_i x_{t-i} \ , where \ \sum_{i=0}^{\infty} |\phi_i| < \infty$$

Thus, causality and invertibility are complementary properties of a given process. In the following the example of an AR(1) and a MA(1) are considered. By repeatedly substituting the representation both processes can be transformed into a MA(∞) representation and an AR(∞) representation, respectively.

In the case of an AR(1):

$$\begin{aligned}
x_t &= \epsilon_t + \phi_1 x_{t-1} = \epsilon_t + \phi_1(\epsilon_{t-1} + \phi_1 x_{t-2}) = \dots \\
&= \epsilon_t + \sum_{i=1}^{\infty} \phi_1^i \epsilon_{t-i} = \sum_{i=0}^{\infty} \phi_1^i \epsilon_{t-i} \\
\Rightarrow Var(x_t) &= E(\sum_{i=0}^{\infty} \phi_1^i \epsilon_{t-i} \cdot \sum_{i=0}^{\infty} \phi_1^i \epsilon_{t-i}) = \sum_{i=0}^{\infty} \phi_1^{2i}
\end{aligned}$$

The series only converges for $|\phi_1| < 1$. Under this condition the AR(1) process can be represented by a stationary and causal MA(∞) process. In the case of a MA(1):

$$\begin{aligned}
x_t &= \epsilon_t + \theta_1 \epsilon_{t-1} \\
\Rightarrow \epsilon_t &= x_t - \theta_1 \epsilon_{t-1} = x_t - \theta_1(x_{t-1} - \theta_1 \epsilon_{t-2}) = \dots \\
&= \sum_{i=0}^{\infty} \theta_1^i x_{t-i}
\end{aligned}$$

The invertibility condition ($\sum_{i=0}^{\infty} |\phi_i| < \infty$) is only fullfilled for $|\theta_1| < 1$. Under this condition the MA(1) can be represented as an AR(∞) process.

C.2 Stationarity condition of an ARMA process

Using the polynomial representation of a general ARMA(p, q) process it is straightforward to see that the stationarity of the process is entirely determined by the AR polynomial $\phi(L)$:

$$\begin{aligned}
& \phi(L) x_t = \theta(L) \epsilon_t \\
\Leftrightarrow\ & (1 - \lambda_1 L)^{n_1} \cdot \ldots (1 - \lambda_p L)^{n_p} x_t = \theta(L) \epsilon_t \\
\Leftrightarrow\ & x_t = \theta(L)(1 - \lambda_1 L)^{-n_1} \cdot \ldots (1 - \lambda_p L)^{-n_p} \epsilon_t \\
\Leftrightarrow\ & x_t = \theta(L) \phi^{-1}(L) \epsilon_t
\end{aligned}$$

The resulting MA(∞) representation is stationary if the coefficients are absolutely summable. The q coefficients of the $\theta(L)$ polynomial are absolutely summable. However, the polynomial $\phi^{-1}(L)$ has generally an infinite number of coefficients. This series of coefficients is absolutely summable only if the root of the AR polynomial $\phi(L)$ are all outside the unit circle in the complex plane. In this case the representation is also causal.

Following the same argumentation with the exchanged role of x_t and ϵ_t

it is shown that the invertibility of an ARMA process is determined entirely by its MA polynomial. Only if the roots of the MA polynomial $\theta(L)$ are outside the unit circle the process is invertible.

C.3 Interdependence term in a SARIMA model

The SARIMA model introduced in Section 3.1.6 can be expanded into an ARIMA representation. The following exemplifies this ARMA representation with the example of a SARIMA$(1,0,1) \times (1,0,1)_24$ process:

$$\begin{aligned}
\phi(L)\Phi(L^{24})(x_t) &= \theta(L)\Theta(L^{24})\epsilon_t \\
(1-\phi_1 L)(1-\Phi_1 L^{24})(x_t) &= (1+\theta_1 L)(1+\Theta_1 L^{24})\epsilon_t \\
(1-\phi_1 L-\Phi_1 L^s+\phi_1\Phi_1 L^{25})(x_t) &= (1+\theta_1 L+\Theta_1 L^s+\theta_1\Theta_1 L^{25})\epsilon_t
\end{aligned}$$

The resulting model is an ARMA$(25,25)$ model, with two parameter constraints $\tilde{\phi}_{25} = -\phi_1\Phi_1$ and $\tilde{\theta}_{25} = \theta_1\Theta_1$, respectively. In general, the constraints result in an ARMA$(p+sP, q+sQ)$ representation. Provided the orders p and q are less than the seasonality s the constraints are given by $\tilde{\phi}_{i+j\cdot s} = -\phi_i\Phi_j$ and $\tilde{\theta}_{i+j\cdot s} = \theta_i\Theta_j$.

Appendix D

Data sources

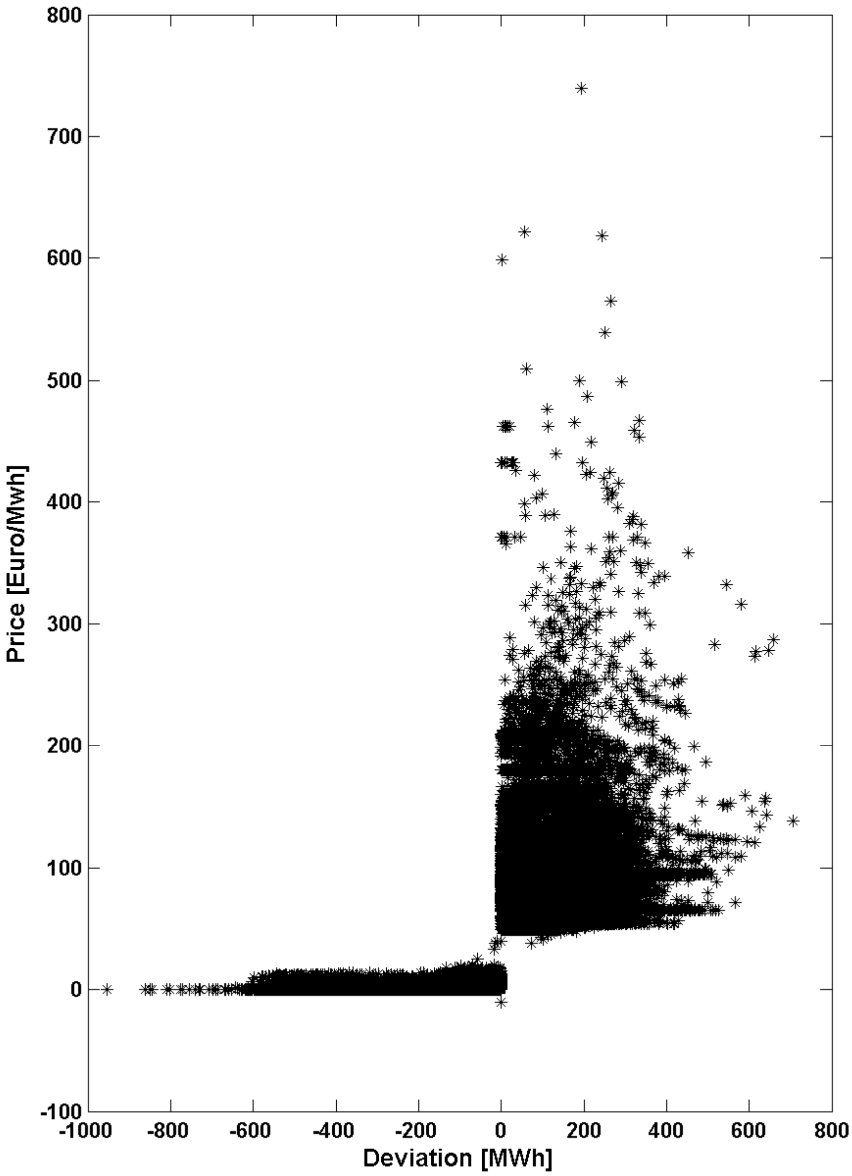
D.1 Balancing energy demand and prices

Germany is subdivided into four control areas that are managed by subsidiaries of the four major players in the German electricity market. (See Figure 2.3.) These subsidiaries act as the TSO in the respective control areas. The control areas' net deviation and balancing energy prices that are fundamental to the billing of balancing energy are published according to the transparency rules of the regulator. This information is conveniently accessed via regelleistung.net (2009) that is a shared platform of the four German TSOs.

RWE Transportnetz Strom/ Ampiron

- RWE Transportnetz Strom is a subsidiary of RWE.
- It manages the largest German control area in terms of load.
- RWE Transportnetz Strom was renamed Amprion in September 2009.
- The data was downloaded from RWE Transportnetz Strom (2009).
- Historical data is available ranging from February 2001 up to today.
- RWE Transportnetz Strom publishes the data in text format providing the control area's net deviation [MW] and the corresponding balancing energy prices [cent/kWh] in quarter-hourly time resolution. Figure D.1 displays the net deviation with the corresponding balancing energy prices.

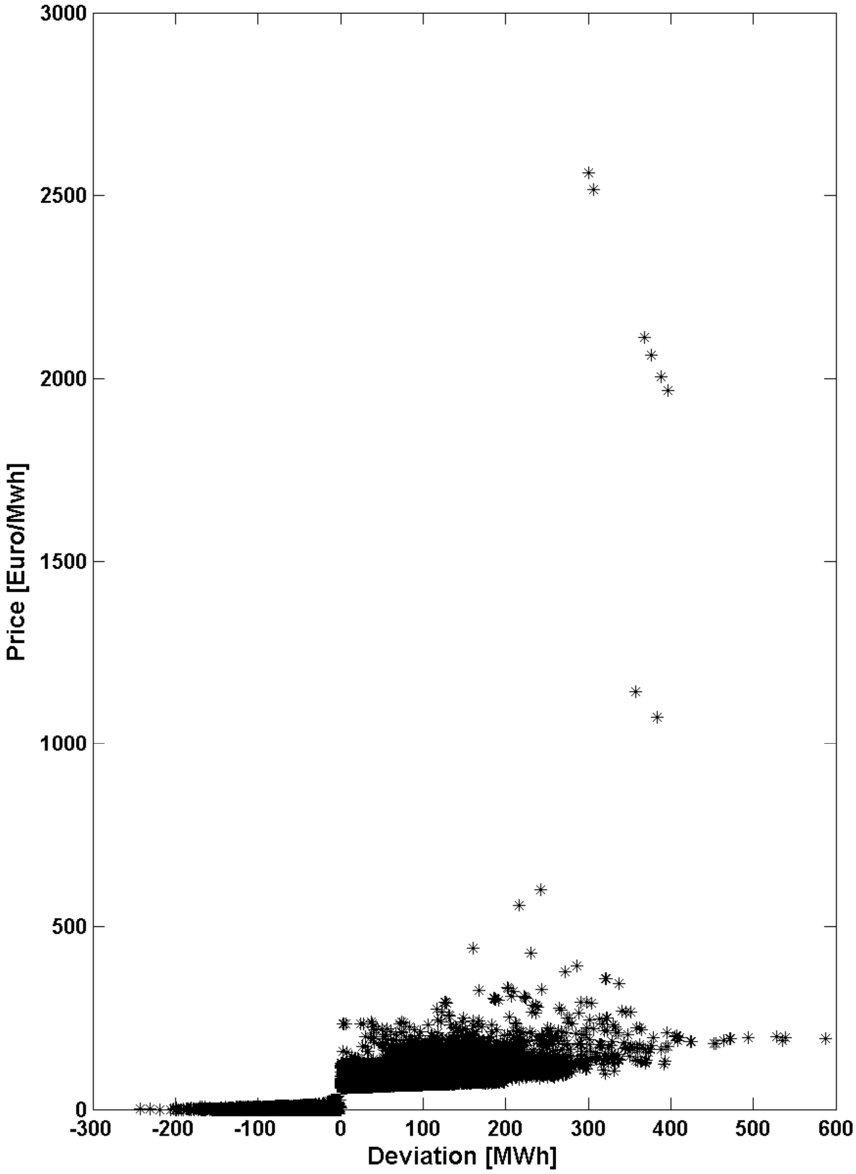
Figure D.1: Balancing energy demand and corresponding prices in the RWE control area from 2003 to 2008



E.ON Netz/ Transpower

- E.ON Netz is a subsidiary of E.ON.
- It manages a large control area in central Germany from the coast to Bavaria.
- E.ON Netz was renamed Transpower in May 2009.
- Transpower was sold to Tennet that is based in the Netherlands in January 2010.
- The data was downloaded from E.ON Netz (2009).
- Historical data is available ranging from December 2001 up to today.
- E.ON Netz publishes the data in monthly MS-Excel files providing the control area's net deviation [MW] and the corresponding balancing energy prices [cent/kWh] in quarter-hourly time resolution. Figure D.2 displays the net deviation with the corresponding balancing energy prices.

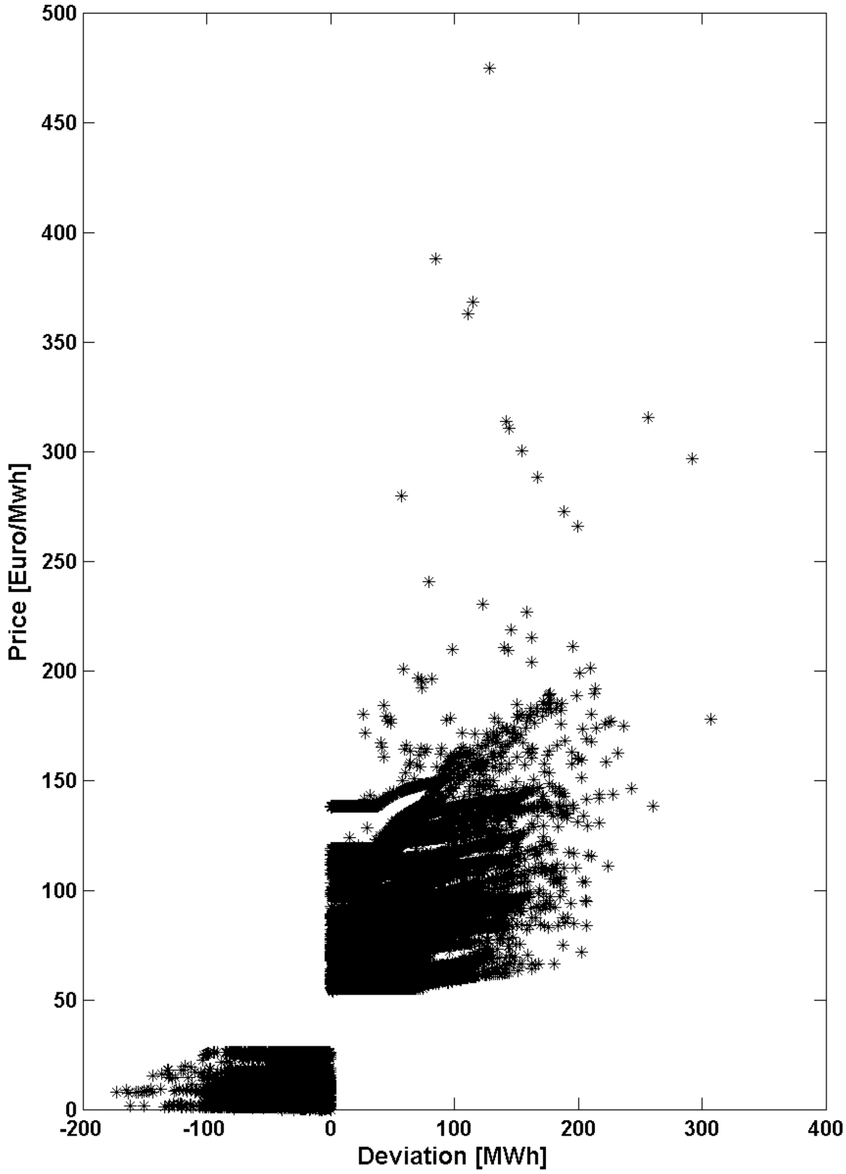
Figure D.2: Balancing energy demand and corresponding prices in the E.ON control area from 2003 to 2008



EnBW Transportnetze

- EnBW Transportnetze Strom is a subsidiary of EnBW.
- It manages the smallest German control area in the South-West of Germany.
- The data was downloaded from EnBW Transportnetze (2009).
- Historical data is available ranging from January 2002 up to today.
- EnBW Transportnetze publishes the data in monthly MS-Excel files providing the control area's net deviation [MW] and the corresponding balancing energy prices [cent/kWh] in quarter-hourly time resolution. Figure D.3 displays the net deviation with the corresponding balancing energy prices.

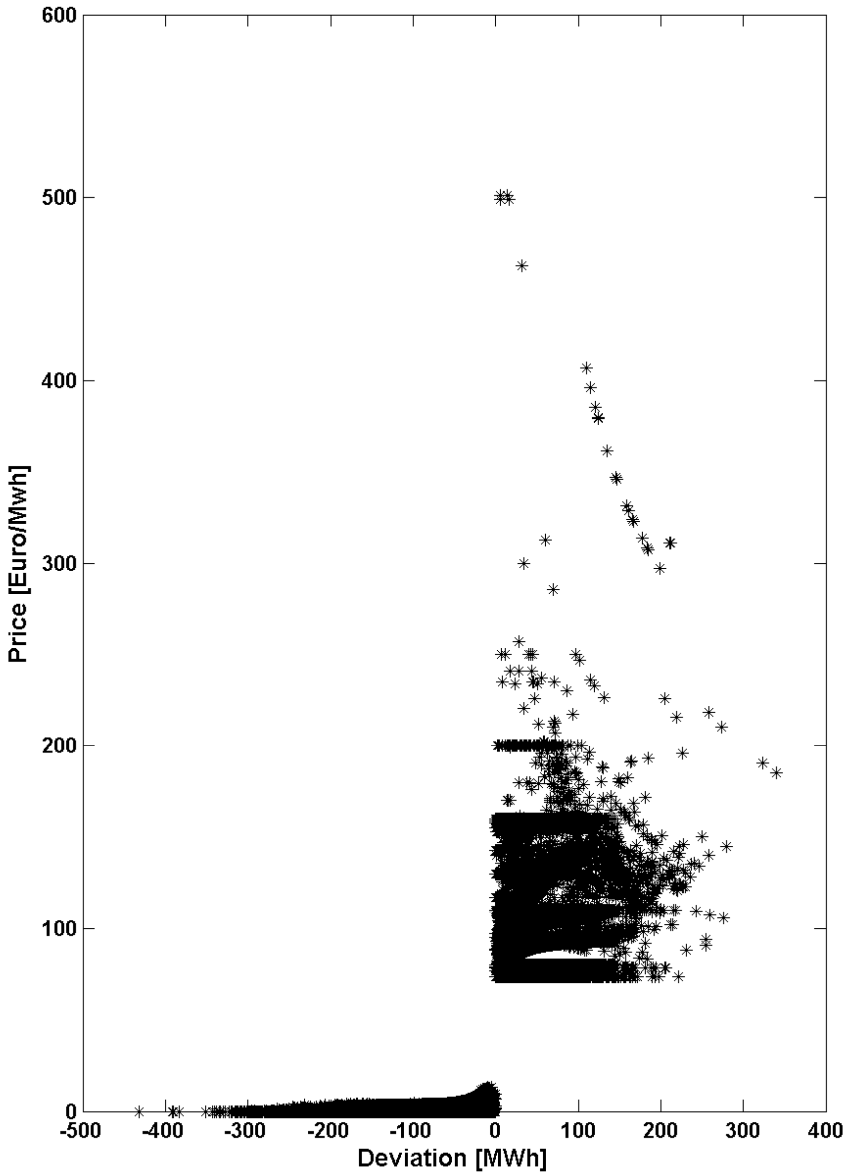
Figure D.3: Balancing energy demand and corresponding prices in the EnBW control area from 2003 to 2008



Vattenfall Europe Transmission/ 50Hertz Transmission

- Vattenfall Europe Transmission is a subsidiary of Vattenfall Europe.
- It manages a control area in the Eastern part of Germany.
- Vattenfall Europe Transmission was renamed 50Hertz Transmission in January 2010.
- 50Hertz Transmission was sold to Elia that is based in Belgium in March 2010.
- The data was downloaded from Vattenfall Europe Transmission (2009a).
- Historical data is available ranging from September 2002 up to today.
- Vattenfall Europe Transmission publishes the data in monthly MS-Excel files providing the control area's net deviation [MW] and the corresponding balancing energy prices [€/MWh] in quarter-hourly time resolution. Figure D.4 displays the net deviation with the corresponding balancing energy prices.

Figure D.4: Balancing energy demand and corresponding prices in the Vattenfall control area from 2003 to 2008

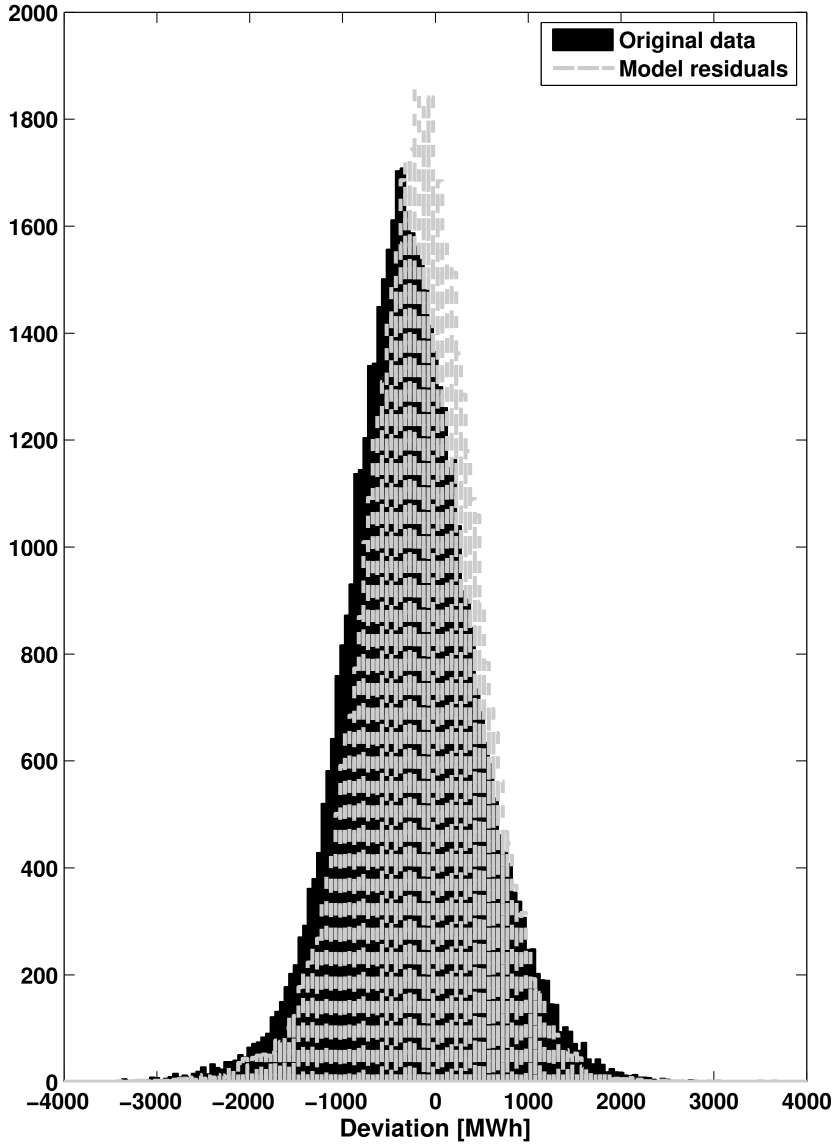


Hypothetical German control area

For the purpose of the analysis in this thesis the balancing energy demand data are combined to the balancing energy demand of a hypothetical single German control area. This German balancing energy demand corresponds best to the single German wholesale electricity market, and is calculated as the sum over the control areas' net deviation of all four German control areas. Implicitly, this approach resolves the issue of control areas presenting countering net deviations because such deviations cancel each other in the sum. Therefore, the combined data treats the German market as a single market as unconstrained by congestions which is the underlying assumption in the wholesale market, as well. Figure D.5 shows the histogram of the original data together with a histogram of the residual of the model applying a one-month forecasting horizon. The less peaked and wider shape of the original data's histogram demonstrate the predictable components. At the same time the residuals' histogram reveals the impact of unpredictable events on balancing energy demand.

Unfortunately, it is not possible to combine the balancing energy prices of the four control areas to a representative price for the hypothetical single German control area. Such a combination has to be based on a weighted average price of the respective four balancing energy prices. However, the weighting of these prices is problematic. Therefore, the analysis resorts to the original prices on a control area specific bases whenever balancing energy prices are needed.

Figure D.5: Histogram of the original data and the model residuals based on hourly values from 2003 to 2008



Regelzonenübergreifender einheitlicher Bilanzausgleichsenergiepreis

The three TSOs EnBW Transportnetze, Transpower (E.ON Netz) and Vattenfall Europe Transmission have combined the settlement procedure of their respective control areas in May 2009. Therefore, deviations in these control areas are settled at a common price, the *Regelzonenübergreifender einheitlicher Bilanzausgleichsenergiepreis (reBAP)*. A company registered as BRP in more than one of the reBAP control areas will settle the respective deviations in the three control areas. However, the common price and the single price settlement put the company effectively in a single control area position. In many respects this combination reduces the number of control areas in Germany to two, the RWE control area and the reBAP control area, with their respective net deviation and balancing energy prices. Moreover, the RWE control area is expected to join into a common settlement scheme in 2010.

D.2 Day-ahead market prices

- The European energy exchange (EEX) is the electricity exchange for the German market.
- The central products are 24 day-ahead futures of hourly delivery and day-ahead base (24/7 delivery) and peak (weekdays 8-20) contracts.
- In addition, monthly, quarterly, and yearly futures are derived from these day-ahead contracts.
- The data was downloaded from European Energy Exchange (2009).
- Historical data is available ranging from September 2001 up to today.
- EEX publishes the data in weekly html-files providing hourly prices [€/MWh] and the corresponding trading volume [MWh]. Table D.1 gives an overview of the prices that occurred in the years analyzed.
- The market features a 0 €/MWh and a 3000 €/MWh price cap.
- In September 2008 negative prices were introduced in the market and the lower price cap was changed to −3000 €/MWh. The first occurrence of negative prices was in late December 2008.
- As typical for electricity markets, the prices display a strong load dependence and corresponding seasonality that is evident in Appendix E.2 and Figure D.6.

Figure D.6: Sample of hourly electricity prices in a week

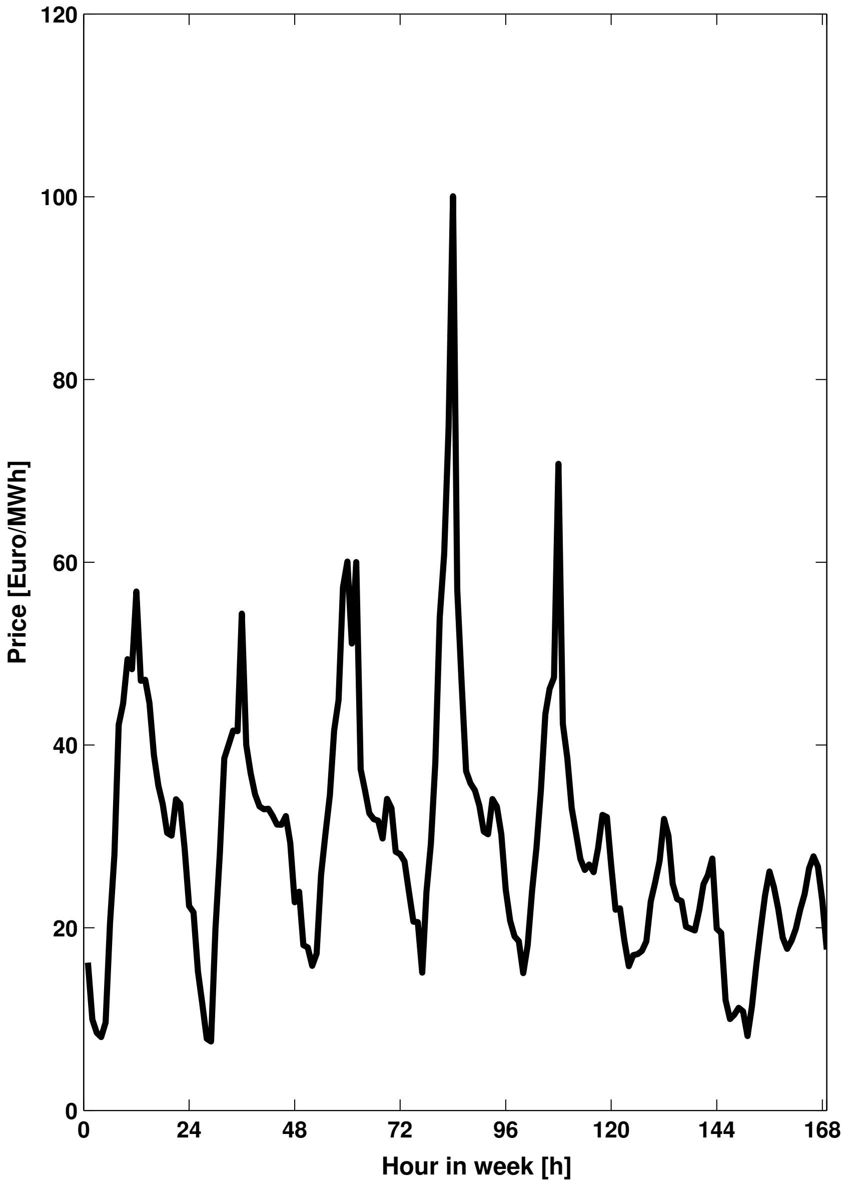


Table D.1: Prices at the EEX from 2003 to 2008 based on EEX clearing prices.

	Price statistic [€/MWh]			
Year	Mean	Std. deviation	Minimum	Maximum
2003	29.49	26.49	0.00	1719.72
2004	28.52	10.80	0.45	149.96
2005	45.98	27.22	0.00	500.04
2006	50.79	49.42	0.00	2436.63
2007	37.99	30.35	0.00	821.90
2008	65.76	28.65	-101.52	494.26

D.3 Demand data

The electricity supply and demand are key factors in electricity markets because the instantaneous equilibrium of supply and demand transfers the dynamics of the electricity demand directly to the dynamics of electricity prices. This relationship allows to calculate the electricity demand as the sum of electricity produced in a given time period and area if electricity imports and exports are also accounted for. In turn, the supply side can be estimated by the installed capacity because capacity extensions happen gradually over extended periods of time. However, the availability of capacity has to be taken into account. In the case of the German market the availability of the base-load nuclear and lignite units is of particular importance. Their maintenance is typically concentrated in the summer month when their capacity is not dispensable for the security of supply. The data described in Section D.3.1 was supplemented by a similar 2004 load measurement in quarter-hourly time resolution provided by the University of Karlsuhe IIP (2008) to allow the in-depth analysis of the quarter-hourly pattern in Section 4.3.

D.3.1 Production, consumption, and exchange package

- The Union for the Co-ordination of Transmission of Electricity (UCTE) is responsible for the coordination of Central European electricity networks.

- It provides an extensive data base including country specific so-called production, consumption, exchange packages. These packages include hourly load data [MW] of the third Wednesday of each month and monthly consumption and production data [GWh].

- The UCTE and other unions of European TSOs formed the European Network of Transmission System Operators for Electricity (ENTSO-E) in July 2009.
- The data was downloaded in the production, consumption, exchange package from *https://www.entsoe.eu*.
- Historical data is available ranging from September 2000 up to today.
- From 2006 onwards the data includes hourly load values for all days. Also, the monthly production of lignite power plants is given.
- The availability is estimated by the monthly generation of nuclear and lignite power stations over the theoretical value of generation at full capacity.
- For the years 2003 to 2005 hourly load values are approximated by transferring the hour of the week seasonality of the years 2006 to 2008, while observing the total monthly generation.

Table D.2: Electricity consumption and production in Germany from 2003 to 2008 based on the UCTE data

	Consumption [TWh]	Production [TWh]				
		Total	Thermal			Renewables
Year	Total	Total	Nuclear	Lignite	Other	& Others
2003	544	560	155	351		22
2004	553	569	158	387		25
2005	556	574	155	358		62
2006	559	588	159	137	222	70
2007	556	584	133	140	226	85
2008	557	587	141	138	218	90

Appendix E

Interplay with marketplaces

E.1 Apportioning of quarter-hourly pattern gains

Figure E.1: Contribution to the quarter-hourly strategy in the E.ON control area

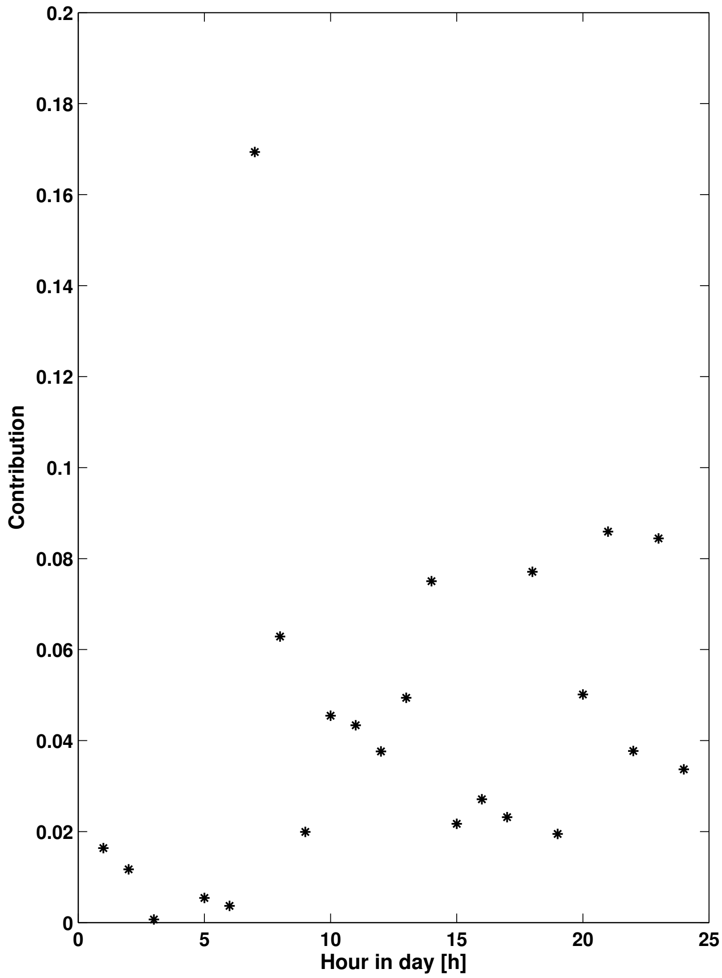


Figure E.2: Contribution to the quarter-hourly strategy in the EnBW control area

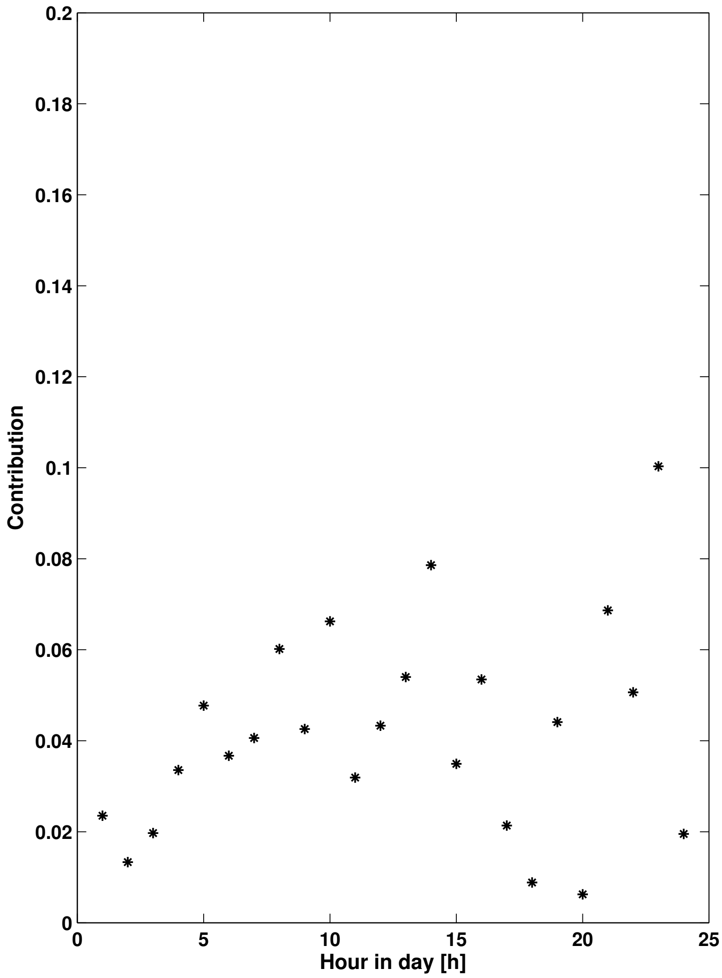
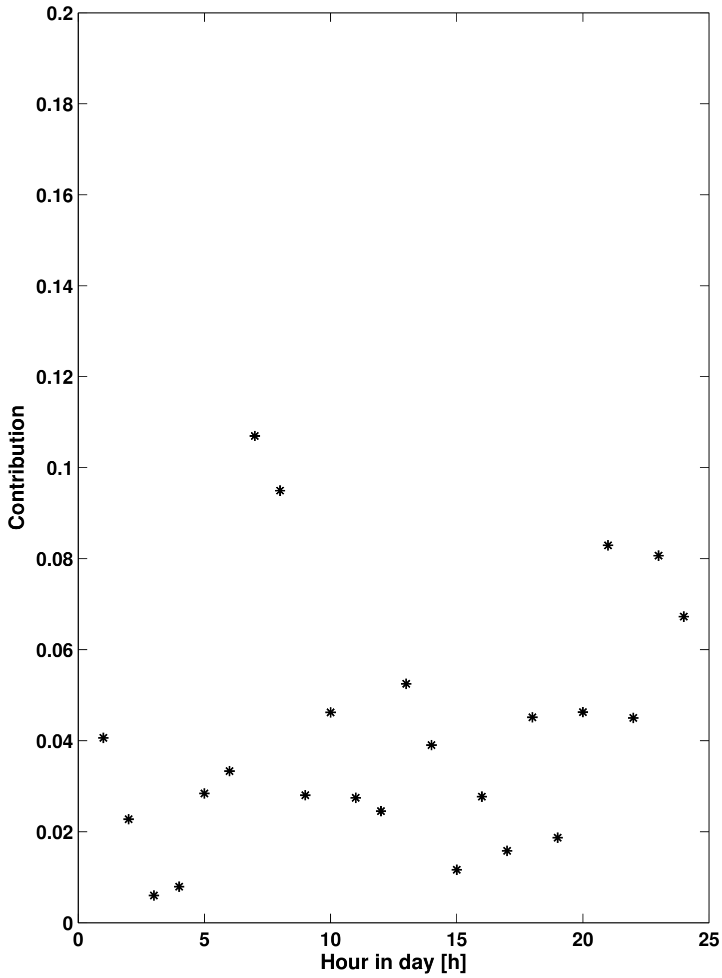


Figure E.3: Contribution to the quarter-hourly strategy in the Vattenfall control area



E.2 Data basis: price load curves

Figure E.4: Electricity prices and estimated equivalent load in 2003

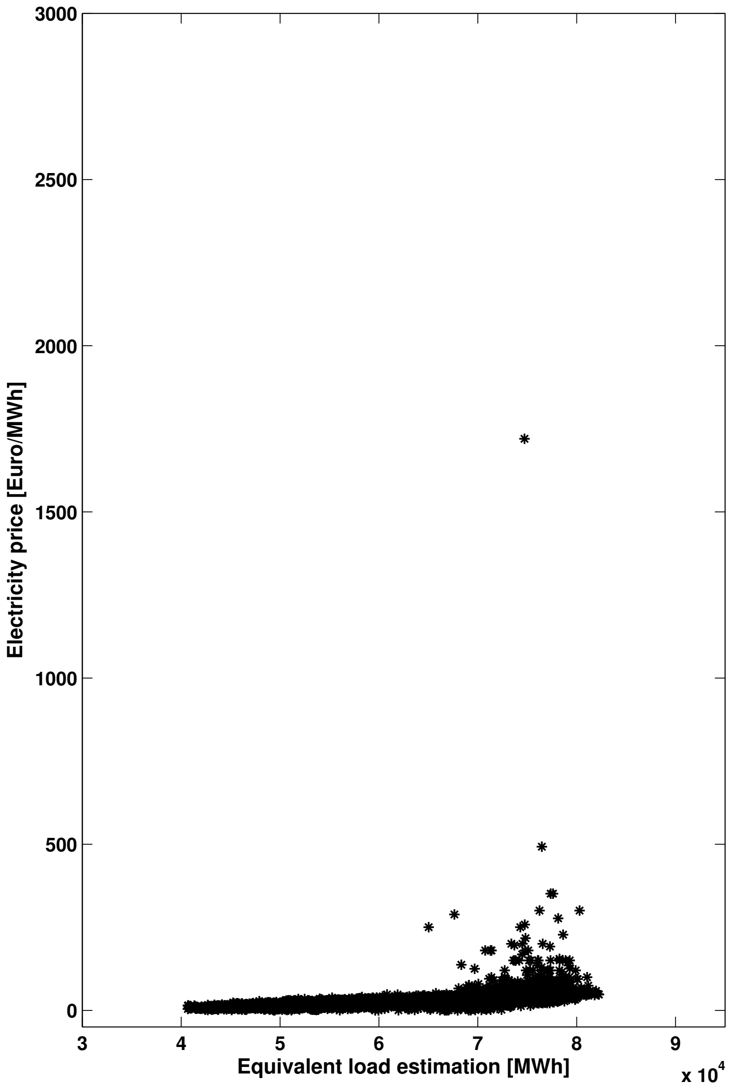


Figure E.5: Electricity prices and estimated equivalent load in 2004

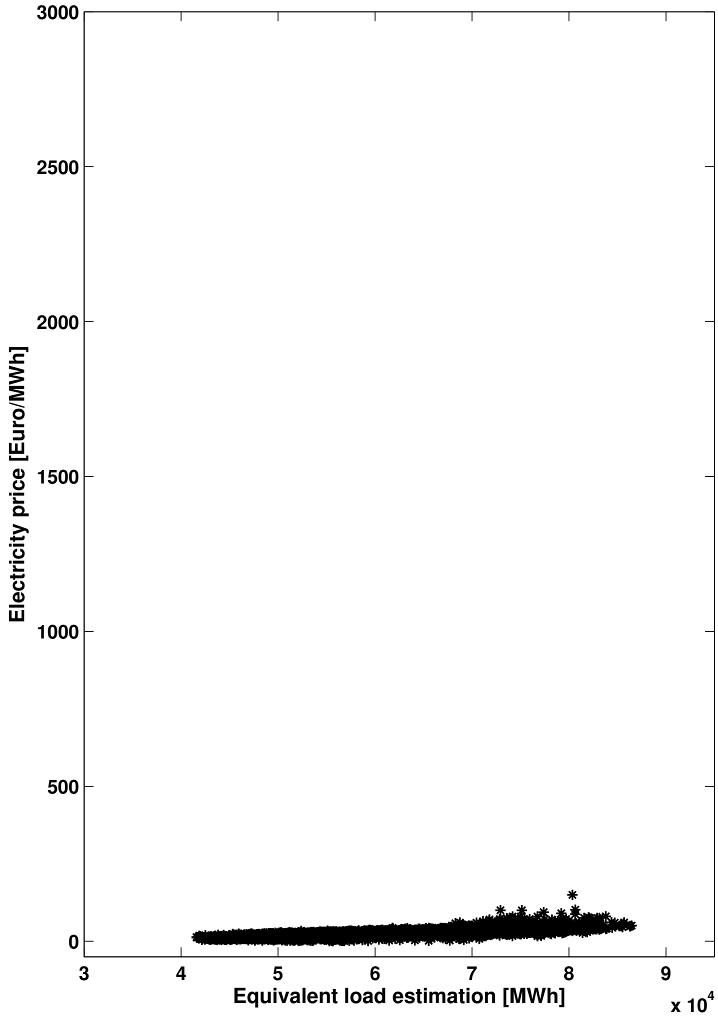


Figure E.6: Electricity prices and estimated equivalent load in 2005

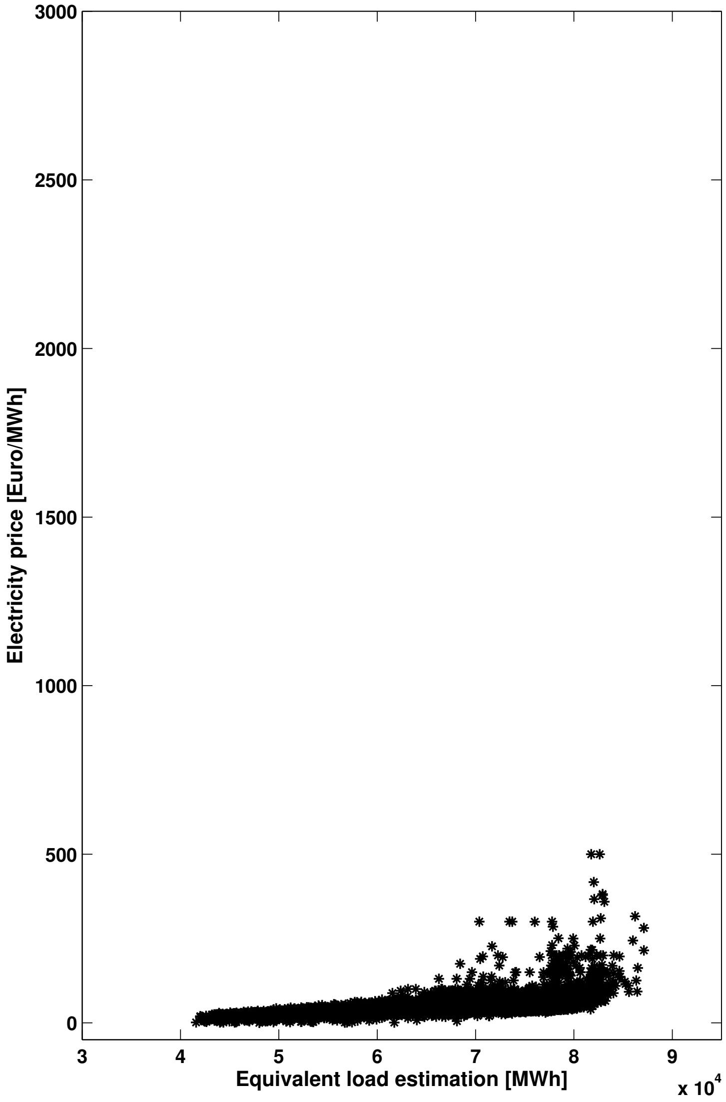


Figure E.7: Electricity prices and estimated equivalent load in 2006

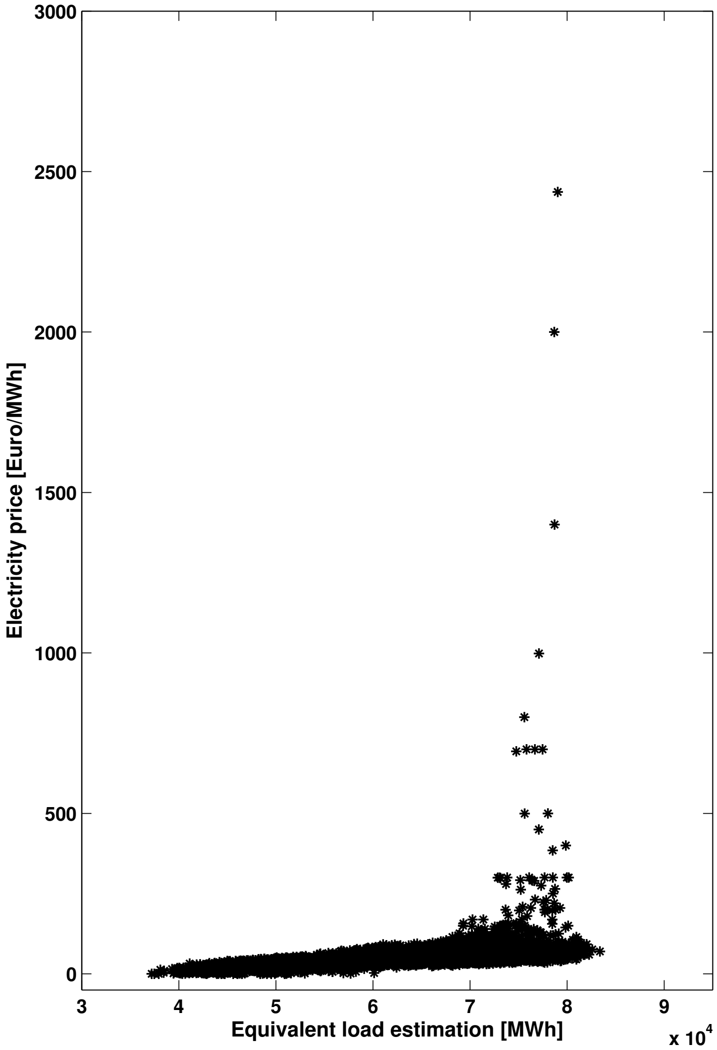


Figure E.8: Electricity prices and estimated equivalent load in 2007

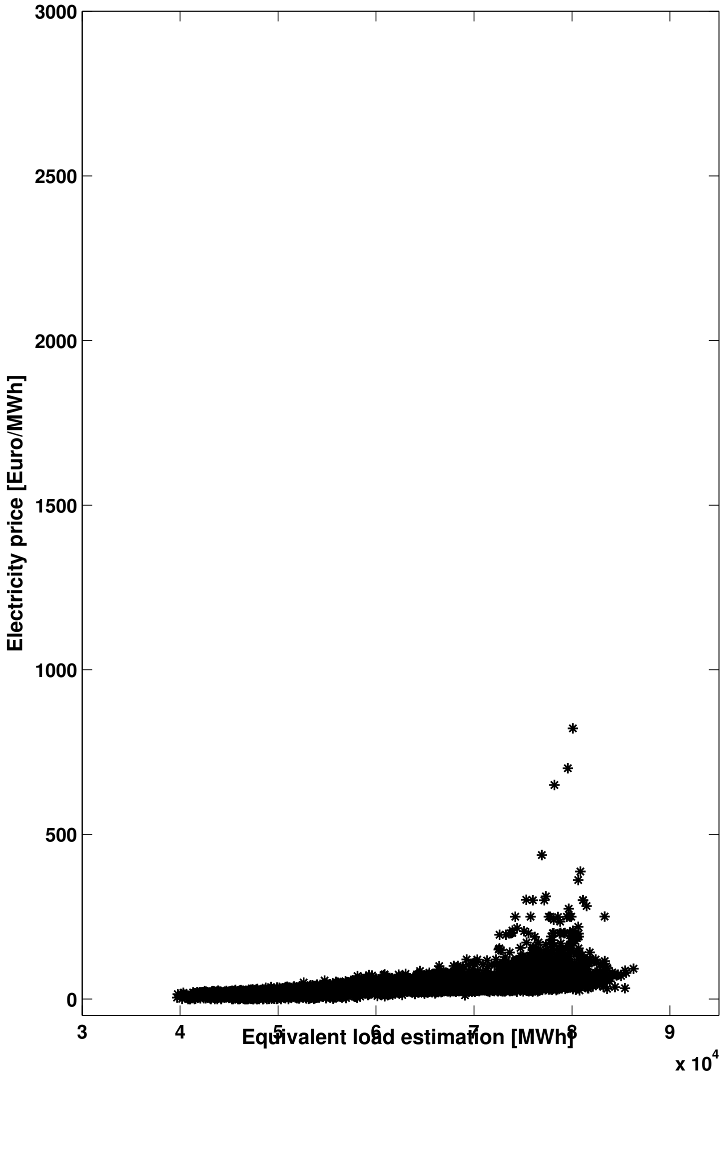
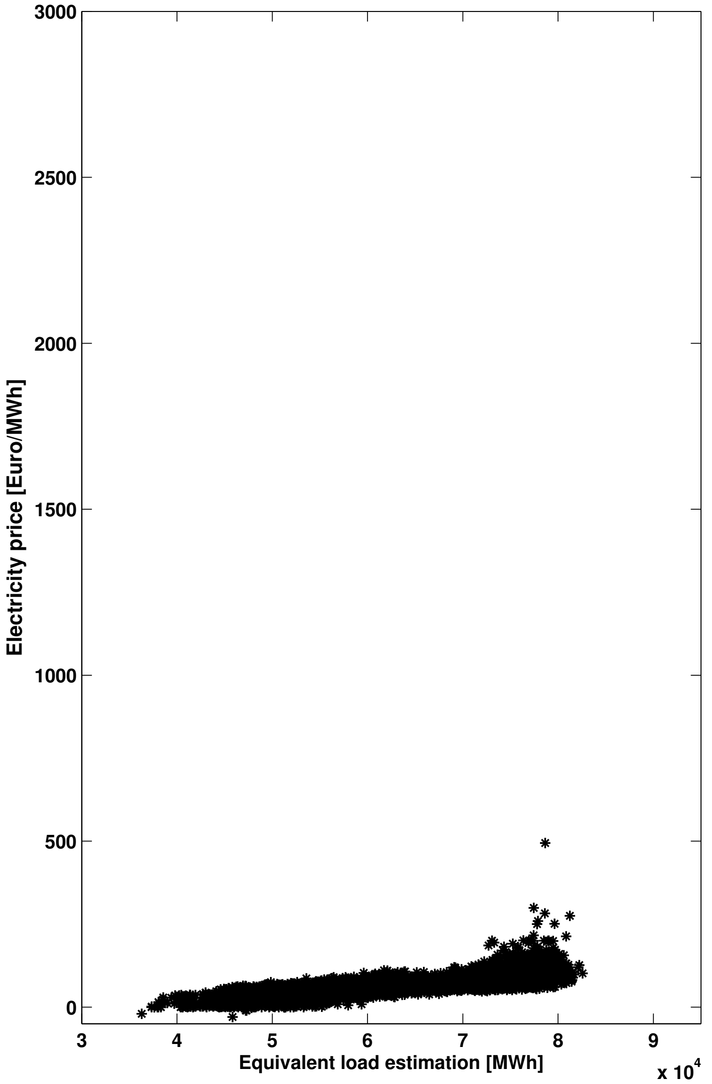


Figure E.9: Electricity prices and estimated equivalent load in 2008



E.3 Balancing energy cost functions in the control areas

Figure E.10: Yearly average balancing energy cost conditional on the net deviation in the E.ON control area

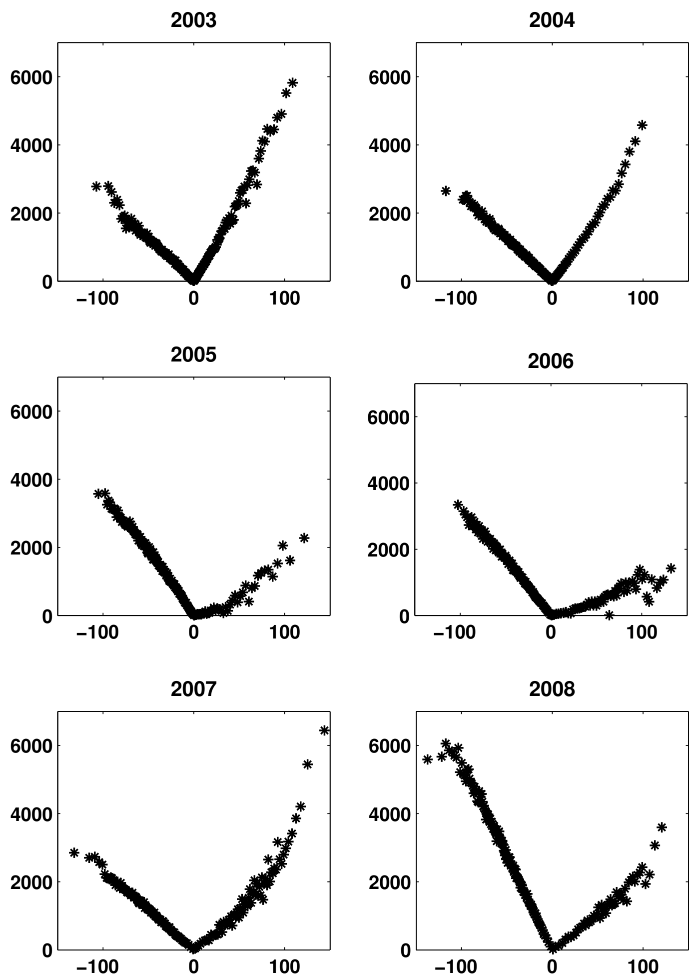


Figure E.11: Yearly average balancing energy cost conditional on the net deviation in the EnBW control area

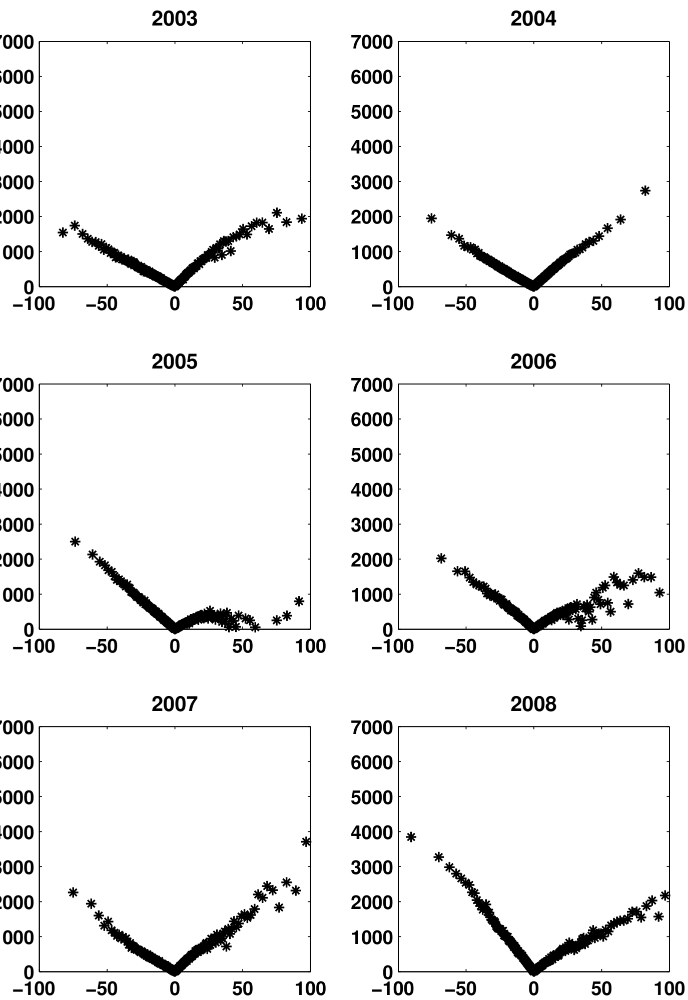
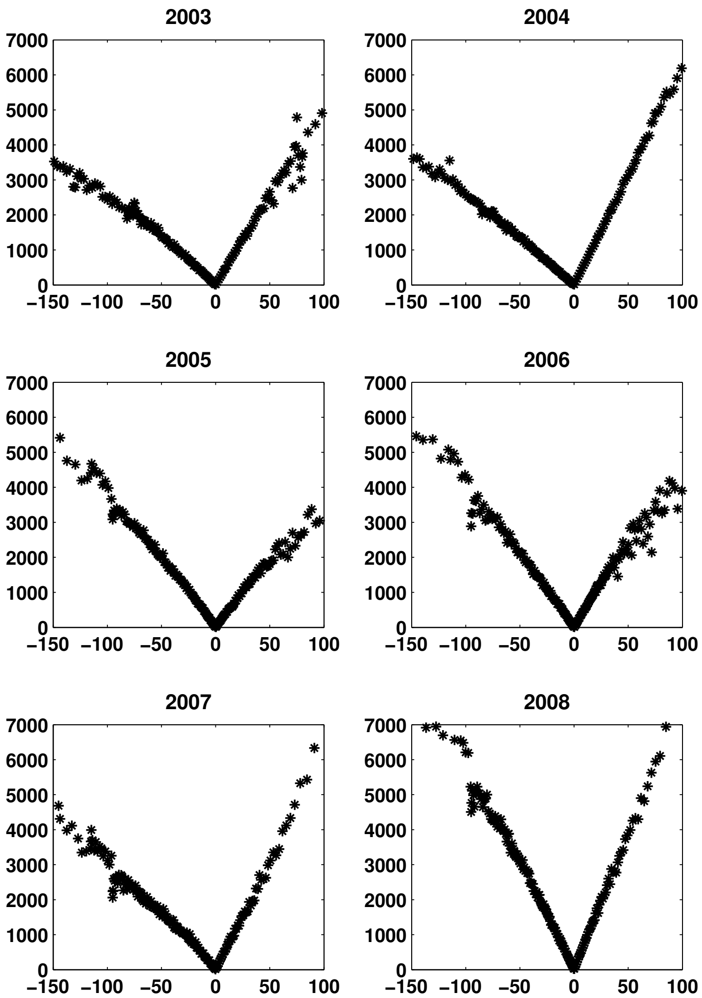


Figure E.12: Yearly average balancing energy cost conditional the on net deviation in the Vattenfall control area



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