The Economics of Wholesale Electricity Markets

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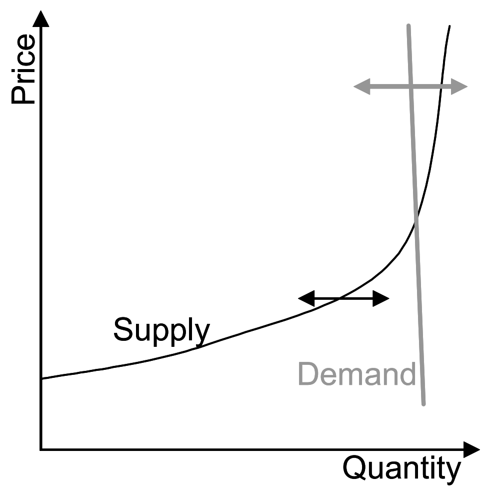
1 Introduction

Electric power markets worldwide are undergoing a dramatic transformation as vertically integrated regulated monopolies are broken up. Some markets, such as the generation market, are being opened completely for competition. This development deserves a thorough analysis due to the sheer size of the market; the electric power industry is a billion dollar industry: the wholesale market in Germany alone has an annual volume of more than 16 billion Euros. Investment costs for a single power plant can exceed 1 billion Euros; these costs are earned over a lifetime of more than 30 years. Market participants need the best tools available to help them assess the market when they want to act on it. However, size is not the only reason for analyzing electricity markets in detail. In addition, electricity generation markets are complex and fragile. Müsgens and Ockenfels (2006) show the importance of a proper market design for electricity markets and discuss the vulnerability of these markets. This vulnerability became apparent to the public when a complete market failure occurred in California around the year 2000. Hence, a thorough understanding of the power market's economics is crucial to an optimal market design and optimal investment and trading decisions by the market participants.

Electricity markets differ from many other markets in several respects. Electricity is not economically storable on a large scale. In addition, supply and demand have to match exactly to prevent costly blackouts and damage to appliances. Furthermore, variable costs differ widely between plants and technologies. Neither demand nor supply is constant over time. These characteristics of the market are displayed in Figure 1.

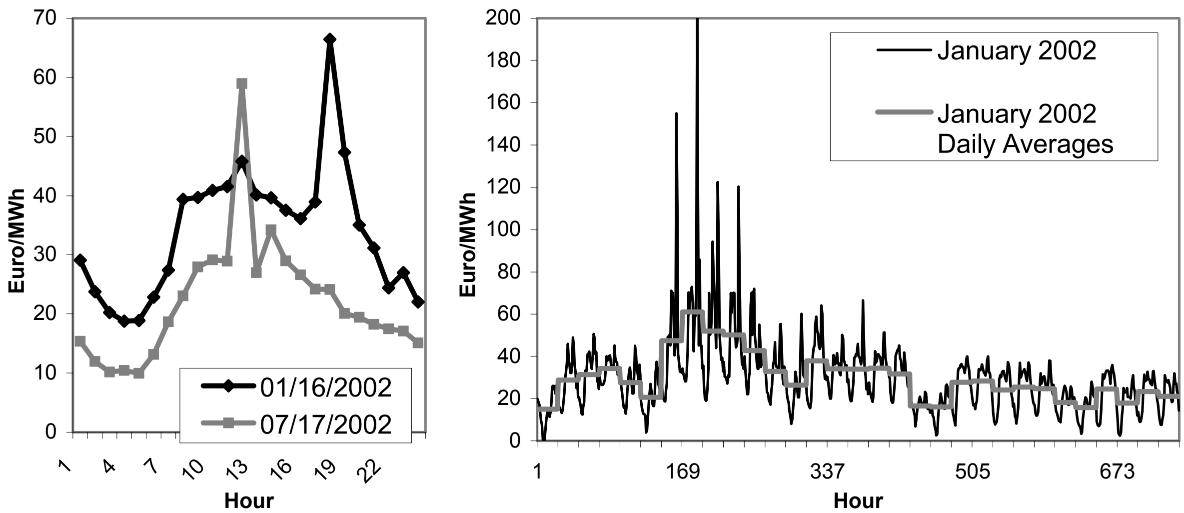
Figure 1: Supply and Demand on Electricity Markets (Schematic)



The supply function is influenced by numerous factors. Among the most important is the installed generation capacity. Not all of the installed capacity is available for production. Installed capacity can be unavailable due to unplanned outages or planned revisions for repair and maintenance. Fuel prices (divided by a power plant's efficiency) determine the largest part of the variable generation costs. The opportunity costs of CO_2-certificates increase fuel prices. Cross border power trade must also be considered. In addition, the supply function exhibits dynamic interdependencies. Power plants have to be started before they can operate. The costs for this start-up are independent of the following duration of operation, thus adding a dynamic component to the optimization problem. Hydro storage and pump storage production are a further dynamic component. On the demand side, the load varies significantly over time and exhibits strong seasonalities on a daily, weekly, and annual level. Furthermore, both demand and supply (unplanned outages) are stochastic. For this reason, some capacity is needed to meet reserve and balancing requirements. The share of capacity providing these services is not available for the wholesale market, however.

The properties described above lead to both seasonality and volatility in prices. Figure 2 shows how this complex interaction of supply and demand is reflected in hourly electricity prices.

Figure 2: Examples for Seasonality and Volatility in Hourly German Electricity Prices



Source: Müsgens and Ockenfels (2006)

1.1 Key Issues and Relevance

The main part of this dissertation presents quantitative assessments of wholesale electricity markets. We develop different models to capture most of the features mentioned above as crucial to both the supply and the demand side of electricity markets. These models are technological bottom-up models calculating market results (costs, prices, power plant utilization, international power exchange, CO_2-emissions…) from input data. The models are optimization models with cost minimization as objective function. A key contribution is the mapping of several potentially non-linear features such as non-convexities and uncertainties into a linear framework. The linear framework allows us to include the large amount of available market data in the model while still modeling the important structural features of the market (international power exchange, dynamic effects of start-up decisions, hydro storage and pump storage dispatch, as well as reserve and balancing requirements due to uncertainty). The results of the models are compared to observed market data whenever possible to check the quality of the models.

We present two major empirical applications in this dissertation. The first is a competitive benchmarking study quantifying the degree of market power in the German electricity generating market. The second is the evaluation of the reserve and balancing costs caused by uncertainties in the wind forecast. Furthermore, we quantify the effects of including some non-convexities in our analysis, using the example of the German market. We benchmark model runs including start-up costs as well as flexible hydro storage and pump storage generation with model runs neglecting these effects. The same is done with cross-border international power exchange, which is of vital importance for the centrally located German power market.

These empirical assessments led to an interesting result which motivated us to perform a formal analysis of start-up costs. We found that start-up costs (the costs associated with starting up a plant such as the cost of pre-heating the boiler and synchronizing the plant with the grid) significantly influence the structure of prices but not the average price. This result is highly relevant in the context of competitive benchmarking studies, as it shows that the effects of start-up costs are negligible as long as a long consecutive time period is analyzed. On the other hand, start-up costs greatly change the structure of prices and the results of such studies when the analysis is limited to selected periods (e.g. high or low demand periods).

A key feature of our approach is the inclusion of several non-convexities which have been neglected in most previous market studies. This was critized in the context of competitive benchmarking studies during California's electricity crisis by Harvey and Hogan (2001) – with a prompt reply by Joskow and Kahn. This debate culminated after several iterations in Joskow and Kahn (2002a). Among other things, Harvey and Hogan pointed out that variable generation costs alone are not an appropriate estimate of marginal costs. Opportunity costs for international power exchange and hydro storage capacity as well as start-up costs have to be considered, too. Competitive benchmarking studies have improved significantly since then (see the beginning of chapter 3 for a detailed discussion); ours is the first dynamic competitive benchmarking study, however, that endogenously models the effects of start-up costs, international power exchange, and hydro storage and pump storage optimization.

The dissertation's academic contribution is the development of economic market models for electricity markets. We go beyond previous work in several aspects, for example by including non-convexities and uncertainty. These extensions allow a much more realistic modeling of the economics of electricity markets. The empirical applications of the theoretical models make the work relevant in practice, too: firstly, the model algebra used to calculate prices clarifies the structure, relationship, and dependency of the electricity market's main driving factors, the understanding of which is essential for all market participants; secondly, the modeling framework we present can be used to answer numerous questions; the models are able to give quantitative answers to specific questions such as: how much would electricity prices rise if the gas price increased by 20%? What would happen to electricity prices if the amount of CO_2-allowances were reduced in the period 2008-2012? What would the effect on hard coal plants (or even a certain unit) be, in terms of generation as well as profits? In the past, similar models have been used to determine the value of a major German electricity generation company's physical assets. In another application, the value – and the effect on electricity prices – of additional interconnector capacity between France and Italy has been determined.[1] The models are also very strong in sensitivity and scenario analysis.

1 Haubrich et al. 2001

1.2 Procedure and Main Results

This dissertation is based on four articles. Chapter 2 is based on Growitsch and Müsgens (2005). In this chapter, we analyze the development of household electricity prices since the liberalization of the market in 1998. The chapter covers all components of the price, the wholesale component, and the transportation and distribution networks. We also discuss the developments of taxes and subsidies in the electricity market. The main result is that the liberalization appears to have had no significant impact on total consumer prices, as prices in 2004 are nearly the same as in 1998.

However, a deeper analysis reveals significant differences between the price components: wholesale prices, which are at the focus of the other chapters in this dissertation, decreased significantly directly after the liberalization took place, but increased from 2001 to 2004. The latter effect is discussed in chapter 3. Despite this increase, wholesale prices are still lower in 2004 than they were in 1998. The costs for transportation and distribution networks decreased slightly but steadily over time. The prices of other cost components (Renewable energy act, CHP subsidies, taxes…), however, rose sharply after the liberalization. This result has serious implications, as it means that insubstantial reductions in household prices do not reveal much about the success of liberalization or the behavior of the electricity supply industry.

Chapter 3 is based on Müsgens (2006). The chapter presents a model to calculate system marginal costs in electricity markets. The model is a dynamic linear optimization model including start-up costs, hydro storage and pump storage dispatch, and international power exchange in the equations. We apply this model to the German power exchange for the period from June 2000 to June 2003 and perform a competitive benchmarking study. We find that prices are very close to our model-derived competitive benchmark in a first period until August 2001: the difference between prices and benchmark is only 2% in this period. In the following period, observed market prices rise significantly; this rise is not reflected in the competitive benchmark: prices are nearly 50% above the competitive benchmark in this second period. We also show that this deviation mainly comes from the high demand periods in which capacity is scarce. This is in accordance with the theories of market power. Furthermore, the chapter contains several scenarios quantifying the price effects of non-convexities and other dynamic elements.

Chapter 4 is based on Müsgens and Neuhoff (2005). As in chapter 3, we present a linear optimization model to determine the optimal dispatch. The model is extended to allow the analysis of the uncertainty brought into the market by wind power generation. We represent uncertainty by applying stochastic programming with recourse. We parameterize the model with historical data from the German power market and find that the short term costs for the integration of wind power are low, as there is sufficient capacity during most periods to provide balancing services.

Chapter 5 is based on Kuntz and Müsgens (2005). The chapter presents a formal in-depth analysis of the effects of start-up costs on electricity markets. The chapter starts from a simplified version of the optimization problem in chapter 4. Using appropriate transformations (dualization of the original problem, rephrasing the dual and reconverting it into a modified primal problem), we can prove that the impact of start-up costs on the average price is very small, which was already suggested by the empirical analyses in chapters 3 and 4.

Chapter 6 concludes the dissertation.

2 The Economics of Restructuring the German Electricity Market

2.1 Introduction

A worldwide movement towards the liberalization of energy markets took place during the last decade. In accordance with EU law, Germany joined this movement and liberalized electricity and gas markets in 1998 by enacting a new Energy Industry Act. However, in contrast to other European countries, the deregulation of Germany's energy markets had not been associated with the installation of a regulatory agency until July 2005, when the Federal Network Agency started its work. The agency faces a vivid discussion about the German electricity prices; the Association of the Industrial Energy and Power Industry claimed in multiple press releases electricity spot-market prices to be excessive (hypothesis 1) and network charges to be still monopolistic (hypothesis 2). The Association of the Electricity Industry whereas blames the German government for increases in energy prices and refers to high additional costs due to the so called renewable energy act and the promotion of combined heat and power plants (hypothesis 3) as well as – most notably – higher taxes (hypothesis 4).

In this chapter we analyze the development of the German electricity market since liberalization, verifying the hypotheses from above. Therefore, we concentrate the analysis on three major aspects: Firstly, we give an overview of the price development in the different German electricity industry value chain stages since liberalization. Secondly, we present the mechanisms leading to this price development and thirdly, we discuss the underlying market design in three key areas of the market and discuss potential improvements.

Consumer prices are a natural starting point for an analysis of the effects of market liberalization. For that reason, we discuss the development of household customer prices and their components from 1998 to 2004 in subchapter 2.2. This discussion will give an overview of the factors determining electricity prices in Germany and their development in the years since liberalization.

The most important price components will be discussed in detail in the following subchapters. Subchapter 2.3 analyzes wholesale generation prices. We argue that the sharp price decrease from 1998 to 2000 was caused by a shift in the pricing paradigm from average costs to short run marginal costs. We discuss why prices increased again from 2001 onwards subsequently.

Furthermore, we analyze issues of market design in the wholesale generation market. A major focus is put on real time metering, as it could increase the price elasticity of demand which will reduce price spikes as well as restrict the potential for strategic bidding on the supply side of the market.

In contrast to the generation market, both transmission and distribution markets are natural monopolies. Hence, questions of regulation and market design are crucial for an efficient functioning of these markets. The German government enacted the negotiated third party access (NTPA) as institutional frame instead of installing a regulation authority. As competition did not reach the intended level, the European Commission abolished the option of NTPA. Thus, the German government has to replace the current regulatory regime with regulated third party access. The question of how the German transmission and distribution markets should be regulated is currently controversially debated. While it seems inevitable that Germany is going to introduce a regulatory body, the rights of that body, especially with respect to ex-ante or ex-post approval of tariffs, are still debated. Up to now, a cost-plus regulation is in place in the sector. Many other countries made good experiences with incentive/performance based regulation. We analyze the development of network tariffs (in the following access charges) in subchapter 2.4 and give short recommendations concerning the future regulatory system.

In subchapter 2.5, we discuss the influence of politics on electricity prices, focusing on the renewable energy act. Even though the electricity tax causes higher costs per MWh, the renewable energy act is more interesting for a discussion. The main reason is that the act prevents competition in a significant share of the generation market. While the electricity tax mainly influences the demand side of the market by increasing the costs of electricity regardless of its origin, the renewable energy act distorts the dispatch on the supply side by increasing generation from renewable energies while driving competitive thermal capacity out of the market additionally. A similar argument holds for the German ‘combined heat and power act’[2]. However, absolute subsidies paid on behalf of that act are lower and predicted to decline further in the future. Renewable energies supported by the renewable energy act, on

[2] Gesetz für die Erhaltung, die Modernisierung und den Ausbau der Kraft-Wärme-Kopplung (Kraft-Wärme-Kopplungsgesetz)

the other hand, are expected to grow at a steep rate and are hence becoming significantly more important.[3]

2.2 *The Development of Household Prices*

Before analyzing and explaining price developments in different market segments in detail, we show aggregated developments of household prices. Since they tend to show lower price elasticities than industry or commercial consumers and can hence be expected to benefit less from liberalization, they seem to be a reasonable focal point for an economic analysis: if household prices decreased significantly, it can be assumed that other prices declined at least in the same order.[4]

The development of electricity prices for household customers from 1998 to 2004 is shown in Figure 3. The figure distinguishes the different price components adding up to the final consumer price. Looking first at households' total electricity costs, it becomes apparent that prices declined significantly shortly after liberalization but increased again from 2001 on. In 2004, prices have nearly reached the level of 1998.

However, concluding that the liberalization of the German market was not an economic success would be misleading. For one thing, taxes and subsidies have increased significantly. Their share of the final consumer price rose from 25 % in 1998 to 40 % in 2004. This supports the hypotheses 3 and 4, indicating that political decisions increased the electricity prices. Households' total costs for generation, transmission, and distribution in 2004 are still 22 % below their 1998 values. In addition, the success of liberalization cannot be evaluated based on a two year comparison. Both medium and long term effects prevent such simple

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3 The steep growth in volumes will overcompensate the degression in subsidies per MWh.

4 We are abstracting from cross subsidization from households to industry before liberalization.

proceeding. Medium term effects such as fuel prices[5] or hydro and wind availabilities might influence generation costs and prices. Hence, the same price for household customers might be driven by underlying costs in one case but may well be above costs in another. While the first would be an efficient outcome (the good is offered at marginal costs), the second case can contain significant inefficiencies. Hence, especially on the generation side, a comparison of prices and costs is needed. This is what we look at in subchapter 2.3.

Nonetheless, the development of the prices residential customers had to pay for the provision of electricity, namely generation, transmission, and distribution, shows interesting aspects. While the price component for transmission and distribution decreased steadily at a slow rate, the generation price components' development shows more fluctuation. The price households had to pay for generation decreased significantly from 1998 to 2000 (- 65 %), but started to rise again from 2001 onwards. In 2004, they are still significantly below their level from 1998 but have doubled in comparison to their minimum values in 2000. Both the driving factors of generation prices as well as transmission and distribution tariffs will be discussed in the next subchapters.

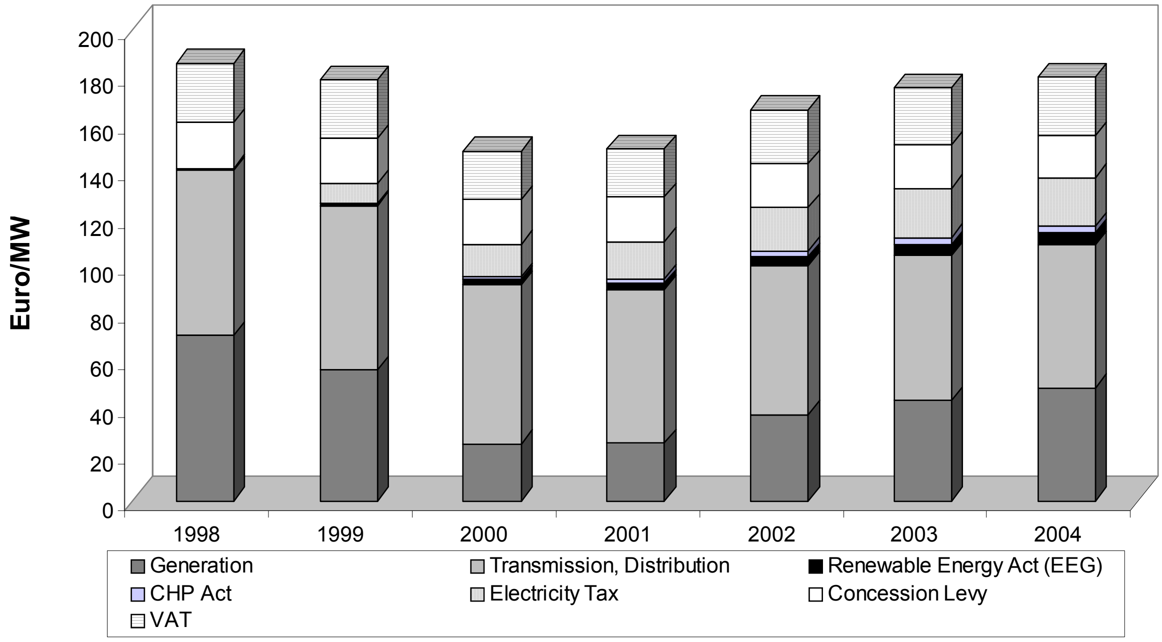
The significant increase in taxes and subsidies is mainly due to the electricity tax which was introduced with the environmental tax reform. Introduced in April 1999 at the amount of 11 $Euro_{2004}$/MWh, this tax and has been increased annually up to 20.85 $Euro_{2004}$/MWh since January 2003.

Another major and growing share of the tax burden on electricity is caused by the renewable energy act. Corresponding taxes increased from 0.87 $Euro_{2004}$/MWh in 1998 to 5.10 $Euro_{2004}$/MWh in 2004. They are predicted to increase further in the future. Besides the already mentioned costs inflicted by the combined heat and power act, there are two more direct and one indirect fees and taxes to mention: Concession levies are paid to municipalities for the right to deliver electricity to the municipality's citizens. While the levy's amount can be determined by the municipalities, a federal decree sets upper limits. The last component of the electricity price in Figure 3 is the value added tax which is 16% during the whole period

5 Hard coal prices can illustrate this point as they nearly doubled from 1998 to 2004. Since hard coal plants are often setting the price in Germany, this development should be included in an assessment of an efficient price structure.

of observation. In addition to the taxes shown the Figure 3, the gas tax should be mentioned, since it increases the costs of fuel for electricity generation. This taxes' effect on electricity prices is included in the wholesale electricity price component.

Figure 3: Development of Electricity Prices, Representative Household Customers, Euro$_{2004}$/MWh



Source: VDEW, EWI

2.3 The Wholesale Generation Market

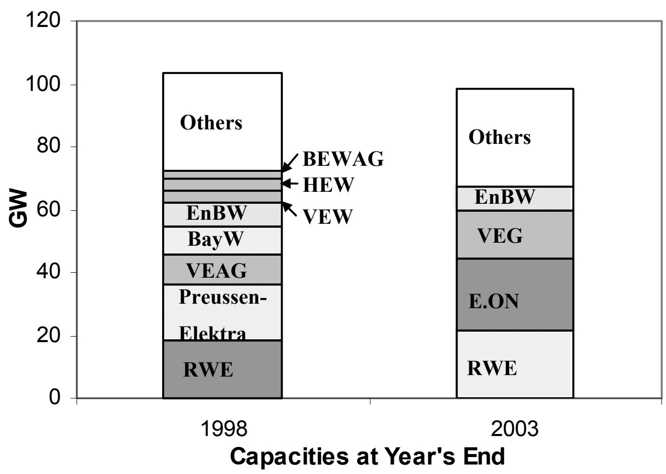
Before the German electricity market was liberalized, wholesale electricity prices were regulated on a cost-plus basis. Vertically integrated generation companies were allowed to charge electricity prices in their regional monopolies sufficient to cover all costs. Hence, the costs households had to pay for electricity generation were determined by average generation costs. It is well known that such a regulatory setting gives incentives for overinvestments. In the case of the German electricity supply industry, there is evidence that this happened.

After liberalization, beginning in 1999 but mainly during 2000, excess capacities and fierce competition brought German wholesale electricity prices down to short run marginal costs. We show in chapter 3 that wholesale prices were at the level of short run marginal costs at least from June 2000, when the first German power exchange started operations, to August

2001. Hence, the huge drop in prices from 1998 to 2000 seems mainly due to a regime shift from average cost pricing to marginal cost pricing.

However, excess capacities on the supply side of the market were reduced gradually. German plant operators took close to 10GW of generation capacity out of the market. On the other hand, new capacity has been installed to a much lower extent. Hence, installed net generation capacity in Germany decreased significantly following the market liberalization.[6] In addition, most capacity additions appeared in subsidized technologies, either combined heat and power plants or renewable energy sources. At the same time, increasing demand in Germany (about 1 % p.a.) further reduced excess capacities. Another factor which has reduced competition in the German market is increasing concentration due to mergers and acquisitions. The number of large generation companies has declined from eight to four. Both decreasing capacities as well as increasing concentration are shown in Figure 2.

Figure 4: Development of Net Generating Capacities in Germany, Excluding Wind and Rail, 1998 and 2003



Source: EWI

The development of prices and marginal costs will be discussed in detail in chapter 3 of this dissertation. In that chapter, we compare prices and competitive short run marginal cost estimators derived with an empirical partial equilibrium model. The key result is shown in

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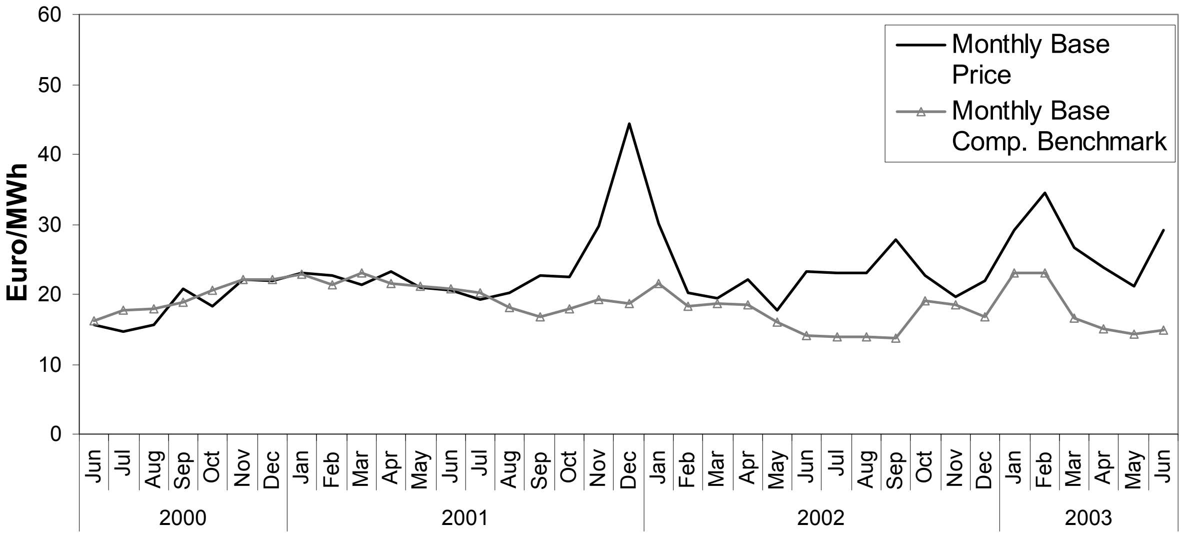
6 The large increase in installed wind power capacity does soften the capacity decrease at first glance. However, due to the large volatility in wind generation, EWI calculated that additional wind power reduces necessary thermal capacity by less than 10 %.

Figure 3. From June 2000 to August 2001, wholesale prices are very close to marginal costs. However, a structural break is identified between August and September 2001. Prices have been significantly above short run marginal costs in the second period since September 2001.

It has often been argued that prices have to be above short run marginal costs since total costs for new capacity could not be covered otherwise. However, this is not necessarily true. We understand marginal costs as the intersection of supply and demand, which can be above generation costs of the last inframarginal unit. If demand reaches a binding capacity constraint, the supply function is vertical and the elasticity of demand determines the price. In such a case, prices can – and will in equilibrium – be high enough to cover all costs for new investments. Hence, prices equal to short run marginal costs understood the way described above would be an efficient scarcity price signal.[7] Following this line of argument, the difference between marginal costs and prices described in Figure 3 means a loss in social welfare.

Figure 5: Marginal Costs and Prices in the German Wholesale Market



However, it is questionable whether short run marginal cost pricing can work in reality. Three main arguments have been raised against it. Firstly, offering all units at marginal costs is inconsistent with players' profit maximizing behavior as will be described later. Secondly, a

[7] This so called peak load pricing scheme was first presented by Boiteaux in 1949 (in French). An English translation appeared in 1960 (Boiteaux (1960)).

low price elasticity of demand might lead to excessive prices or might even prevent a market clearing. Thirdly, price spikes inherent in this pricing scheme are likely to be unacceptable for regulators and politicians which might prevent investments.

The first argument is probably the strongest. Ausubel and Cramton (2002)[8] showed that bidding at marginal costs is not profit maximizing in a multi unit auction if a company is producing more than one unit – which is the rule and not the exception in electricity markets. On every unit but the first, the bidder has an incentive to raise the bid above marginal costs. If the unit has a positive possibility to be the marginal unit and hence set the price, all inframarginal units will also gain from the higher price. Hence, while short run marginal cost pricing gives an efficient benchmark, it is unlikely to be consistent with individually rational profit maximizing behavior by market participants. A player's incentive for bidding capacity above marginal costs increases with the size of its capacity but decreases with the price elasticity of demand.

However, short run price elasticity of demand is very low in electricity markets. It has been pointed out that the demand side determines the price whenever a binding capacity limit is reached. The low price elasticity of demand leads to excessive price spikes during these hours. Kahn (2002) discusses this problem extensively. He concludes that prices of 6000 USD/MWh might be necessary to cover investment costs for peaking units.[9] We agree with Kahn that the solution to this problem should not be averaging prices above longer periods of time. High prices indicate the scarcity of electricity at peak hours. Consuming electricity at times of scarcity should be expensive since the corresponding costs for additional electricity are very high. However, people will only react on these price signals when they are confronted with them. Hence, Kahn proposes real time metering. Real time metering can be expected to increase the price elasticity of demand. This would soften the price spikes during periods of scarcity. Such a change of electricity pricing seems to be necessary, since the public seems to be highly sensitive to price spikes driving both politicians and regulators to act on their prevention. Investors will be reluctant to invest if they fear that

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8 The first draft of the paper appeared in 1995.

9 It is important to note that these prices are necessary to cover total costs of investments. These prices have been paid before liberalization, but they were 'hidden' in average prices.

prices will be ‘capped’ during the few hours when turnover is high and plants’ investment costs can be amortized.

Given these arguments against marginal cost pricing, it can be argued that prices in fact have to be above short run marginal costs during some hours to cover investment costs for new capacity. However, we have not discussed other sources for revenues besides spot markets so far. Especially capacity markets could be a way to recover investment costs and provide for security of supply.

To sum up, it is possible in principle to estimate both short and long run marginal costs in electricity market due to the relatively good availability of data. Prices above short run marginal costs, as currently observed in Germany, are not necessarily an indication of losses in social welfare considering the problems with short run marginal cost pricing. A fairly complex analysis is needed whether new investments are necessary in the market. If new investments are necessary, expected prices have to cover total costs of technologies entering the market.

We already stated our belief that an increased short run price elasticity of demand (mirroring short run generation costs) is essential for a proper functioning of electricity markets. Real time metering is an important mean to increase the elasticity of demand. Increasing the elasticity of demand will not only reduce price spikes but also lead to less variation in demand over time. This will result in a load profile that is cheaper to serve. In the future, the demand side can also help to absorb a further increase in variation of the load profile brought by an increasing share of wind power in the market.

In addition to that, elasticity of demand will restrict the potential for strategic bidding in electricity markets. The more elastic electricity demand, the less profitable are bidding strategies above marginal costs and the less severe is the loss in welfare associated with strategic bidding. The intuition behind this is that with a higher price elasticity of demand, prices will rise less for a given amount of capacity withdrawn from the market clearly making strategic behavior less beneficial.

A last benefit of real time metering could be an improved outage prevention. Arbitrary customer cut-offs could be replaced by a market based solution: those customers who value electricity the most would be served, other customers not. While outages are currently not a problem in Germany, they might become more important in the future.

A more recent development is the trading of CO_2 emission certificates since the beginning of 2005. Following EU legislation, these certificates were distributed free of charge, based on historic emissions for a reference period (2000-2002). It is efficient and at the heart of the idea of emissions trading that the certificate price translates into higher electricity prices. This is regardless of whether allowances are auctioned in a first step or donated. However, CO_2 prices can be another mean to increase profits on the electricity market: Exercising market power on the certificate market could be a profitable strategy for large electricity suppliers - even if it is not profitable on the CO_2 market because of increased profits on the electricity spot market. It is difficult to assess whether the currently high certificate prices of above 20 Euro/t CO_2 equivalents are the result of market power or based on marginal costs of CO_2 avoidance. While prices below 10 Euros were expected by most studies (e.g. EWI/Prognos 2005), short time frictions in the market might actually lead to higher prices. For example, some countries have still not effectively started trading at all in mid 2005. In addition, short-run costs of CO_2 avoidance might be significantly higher than long run costs.

With respect to the hypothesis of distorted spot prices, we have to draw a mixed conclusion. The analysis showed that prices are above the competitive benchmark for a long period of time. This is a strong indication for strategic behavior in the spot market, consumers are paying too much. On the other hand, prices in the long run equilibrium can be expected to cover total costs in the system. Prices are not considerably above the level of total costs for new generation units. Complexity was added by the beginning of the CO_2 emission certificate trading. Further research is necessary to evaluate whether excessive profits are earned at consumers' cost due to market power on the emissions market or whether high certificate prices are an efficient scarcity signals.

2.4 Transmission and Distribution Prices in Germany

The institutional framework for access to German transmission and distribution networks is based on a set of contracts between energy producers and industrial consumers (associations' agreements; *Verbändevereinbarungen,* abbreviated *VV*), subject to ex-post control by the

Federal cartel office. These agreements implement the EU electricity directive (96/92/EC) and the national energy act 1998 (EnWG), into a system called Negotiated Third Party Access (NTPA). In contrast to the more common regulated third party access, the German regulatory system is not associated with a regulatory agency and a corresponding ex-ante regulation scheme.

In 1998, the first associations' agreement VV I was implemented followed by a modified and expanded agreement VV II in 1999. The final agreement VV II+ replaced the earlier one in 2001 lapsing at the end of 2003. Since then, it was accepted as a general code of practice by law. However, due to the EU acceleration directive from summer 2003, a regulatory authority has had to be appointed until 1 July 2004, replacing negotiated with regulated third party access. However, the German Government missed the installation of a regulatory body until summer of 2005.

The first associations' agreement network access was designed as point-to-point transmission; the access charges were calculated in regard to the so called contract path principle, based on the distance between a supplying power plant and the final customer. This procedure was critized for being anti-competitive, as it was complicated and produced comparatively high transaction costs (Monopoly Commission 2002, p. 527).

Due to political pressure, the next agreement VV II replaced the contract path concept by a model called *access-point tariff* (Brunekreeft 2001), which is rather a postage stamp concept approach.

A paradigmatic change in the orientation of the cartel policy occurred in April 2001 after a review of network access in the German electricity markets. Since ex-post control of the federal cartel office had concentrated on the control of non-discriminatory third party access to the networks (Bundeskartellamt 2001), it changed its focus to the level of access charges, as the charges have been considered to be excessive (Brunekreeft 2004). Taking this development into account, VV II was replaced by VV II +. This latest agreement contains basic principles for the calculation of network tariffs, required their publication and introduced industrial self-regulation (Brunekreeft and Twelemann 2005).

The duty to publish access charges was intended to be the crucial improvement within VV II+ as being a major issue of the design of a (national) comparison market scheme. Aimed to identify comparable network operators, the agreement differentiates three structural features: *population density* (for low voltage networks) or consumption density (for medium and high voltage networks), *cable rate* (which is the percentage of underground lines of the total network), and *East and West Germany*. This scheme categorizes each network operator; the association of system operators publishes network access charges of each operator for typical consumption cases as well as average prices (Monitoring Report 2003). To restrict monopoly power and to induce regulatory threat, network operators whose tariffs are within the upper 30% price bracket of their structural category have to justify the level of their charges at a board of arbitration, if a network user so demands. However, the board has no final power of decision; if the operator and the customer do not find an amicable agreement, the plaintiff has to enforce its claim through the cartel offices (Monopoly Commission 2002, 529), which is responsible for maintaining the common anti-trust instruments against market power abuse (*threat of intervention*).

The development of the electricity network tariffs in Germany since the energy market liberalization in 1998 has been examined by basically two empirical studies: Kühn and Schulz (2002) analyze the tariffs of 78 transmission and distribution companies covering approx. 70% of the German electricity network. They identify for the period 1999 to 2002 two different trends: first, on average, the network charges decreased slightly for all voltage levels. Second, the variance of the charges decreased as well. The authors attribute the latter development to two phenomena: while the expensive network operators reduced their prices over time, the majority of the suppliers kept their charges constant or increased them slightly.

Growitsch and Wein (2004) investigate the network operators' pricing behavior, predicting what behavior could have been expected for the post 2002 period. Since then, the VV II+ increased market transparency, bringing along the common knowledge of explicit intervention prices consequently. They argue that the specific design of the German electricity market, namely ex-post control, market transparency and the limitation of the threat on the upper 30% rule in particular (intervention frontier), induces wrong incentives in the following manner: The knowledge of the intervention frontier makes it rational for any network operators to adjust its price to the intervention frontier price within their structural class. Cheap operators are able to increase their price to the intervention frontier price without taking the risk of becoming part of the upper 30% in price on the other hand. This rationale stabilizes the intervention price from below. An overall increase in prices is prevented by the expensive suppliers' rationale; they can reduce the risk of being part of the most expensive 30% (and suffering enforced price reductions as a consequence) by decreasing their prices converging to the intervention frontier tariff. Therefore, collusion on high prices cannot be stable above the intervention frontier. However, with a decreasing variance in prices, the risk of pricing beyond the intervention frontier becomes irrelevant, as possible losses due to a cartel office intervention gradually disappear.

These theoretical predictions corresponded to observed price developments. Descriptive information on the tariffs' average growth rate of more than 400 suppliers for the time from 2002 to 2003 is reproduced in Table 1. Considering the means of the low voltage(household related) charges, it seems that they decreased between autumn 2002 and 2003: on average, access changes have fallen by 1.5 percentage points, while the median growth rate did not change at all. The maximum growth rate was 31% , while the minimum growth rate (which is the maximum price decrease) was (-) 39% respectively. Overall, the scale of decreasing values is very small. Hence, even if a reduction has genuinely occurred, the averages decrease is not important from an economic point of view.

Table 1: Growth Rate of Low Voltage Access Charges between 2002 and 2003

	change in percent
Mean	-1.524
Median	0.000
Maximum	31.16
Minimum	-38.65
Standard deviation	6.22
N	444

Source: Growitsch and Wein (2004, p. 15)

In multivariate estimations using data for 370 operators, Growitsch and Wein show a highly significant price decrease of expensive suppliers (defined as supplier inside the upper 30% bracket); taking structural differences into account, such operators lowered their tariffs by roughly five percent points for low voltage level networks' access. On the other hand, cheap operators increased their prices by four percentage points . These results indicate strategic behavior of cheap suppliers and confirm the findings of Kühn and Schulz (2002).

Table 2 Growth Rate of Average Access Charges 2002/2003[1]

	Model 1 (low voltage)
Expensive 2002	-5.123*** (-6.296)
Cheap 2002	4.070*** (5.614)
Population density / Consumption density 2002	-0.356* (-1.790)
Cable rate 2002	-0.113* (-1.781)
East-Germany (yes=1)	4.731*** (5.410)
Constant	-0.025 (-0.026)
R^2 (adjusted)	0.212
F-test (P-value)	21.267*** (0.000)
Observations	377
Test of normality after Jarque/Bera[2]	H_0^a*** (0.000)
Test of homoscedasticity according to White[2]	H_0^{na} (0.283)
Estimation method	OLS

*[1]Significant on 10 %-, 5 %-, and 1 %-level: *, **, and ***; t-values in parentheses.*

[2]H_0^a: null hypothesis could be rejected; H_0^{na}: null hypothesis could not be rejected; p-values in parentheses.

Source: Data set 'Deregulated German electricity market'; estimated with EViews 4.0.

Source: Growitsch and Wein (2004, p. 20)

However, recent developments of network tariffs militates for a change in network operators' behavior. Descriptive statistics (table 3) show a slight increase in mean and median network access charges; the standard deviation has also increased (although none of these measures increases by more than one percent).

Table 3 Network Access Charges (Low Voltage) 2004 and 2005: Descriptive Statistics

	2004	**2005**	**change in percent**
Mean	5.466	5.471	0.083
Median	5.380	5.400	0.372
Maximum	7.770	7.770	0.000
Minimum	3.110	3.110	0.000
Standard deviation	0.572	0.577	0.766

Source: own calculations based on figures published by the Association of German System Operators.

From a firm level perspective, VIK (2005) reports an increase in network tariff of up to 20% from 2004 to 2005. Both observations could be interpreted as that the regulatory threat did not hold any more (Brunekreeft and Twelemann 2005) since the installation of a regulatory authority was announced in 2004. Instead, collusion became less reasonable than price increases, network operators seem to build up a "price reduction margin", anticipating price cuts by the regulator.

Recapitulating this subchapter, it can be stated that the German institutional setting of negotiated third party access failed in terms of the aims of liberalization. As it is going to be substituted by regulated third party access soon, we are going to suggest crucial elements of upcoming regulatory setting. Regulation in general, although necessary in utilities industries due to market failures, intervenes into market processes and bears specific risks of distortions and wrong incentives. As it is therefore unavoidably inefficient, it should be restricted to non-competitive (monopolistic) market segments. As any regulator suffers from asymmetric information additionally, a regulatory system should be as least information demanding as possible. The regulatory scheme satisfying these requirements best is from our point of view

Performance-based regulation (PBR, sometimes incentive regulation). This method is an established alternative to the 'traditional' cost of service regulation. While the latter allowed regulated companies to recover costs and a (percentage) surcharge ('cost-plus regulation') PBR establishes competitive market incentives into the regulated markets. Conventional PBR set up a revenue or price cap that is adjusted annually for inflation (RPI) on the one hand side and reduced by potential productivity improvements (X) to give incentives for eliminating efficiencies on the other ('RPI-X' regulation). Consequently, PBR creates strong incentives of cost reduction. However, these cost reductions may have negative impacts on reliability and quality of service. Thus, we suggest a PBR scheme that includes performance indicators related to reliability, market efficiency, and customer service. To allow for an appropriate calculation of the X factor, we recommend international comparison methods (international benchmarking). Given that, PBR is likely to result in reduced cost of regulation, reduced cost of negotiations concerning the distribution of utility cost reductions, and improved risk allocation between utilities and consumers.

2.5 The Renewable Energy Act

In subchapter 2.2, we mentioned that the share of fees and taxes for household customers has increased significantly since 1998 reaching 40 % of total costs in 2004. While taxes are lower for industrial consumers due to several exceptions, the share of regulatory inflicted costs increased due to these raises in the years after deregulation. One - major - reason for this development is the renewable energy act.

The Renewable Energy Act (EEG[10]) was implemented to promote the electricity generation from renewable energy sources (RES) in Germany. The revised version of this act has been enacted August 1st, 2004. The EEG pursuits several goals: Firstly, it aims at climate protection by reducing CO_2-emissions.[11] Secondly, it aims at increasing the long-term security of supply in Germany by reducing the dependence from imported gas and coal. In

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10 **E**rneuerbare **E**nergien **G**esetz

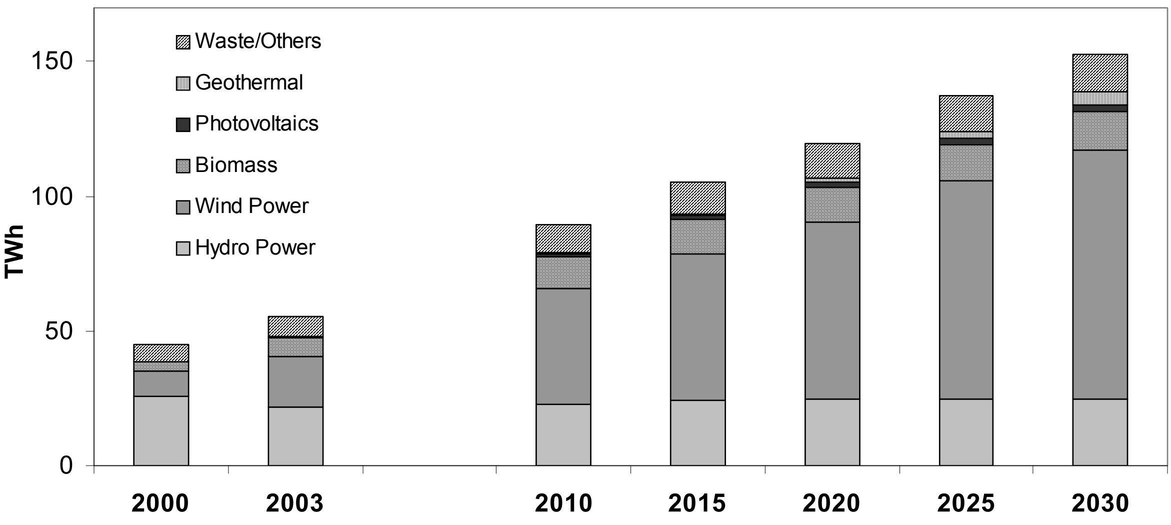
11 Whenever we are talking about CO_2-emissions, we always include other greenhouse gases.

addition, the consumption of finite resources shall be restricted and technological progress in RES generation technologies shall be made. The act also specifies precise targets for RES' share of total electricity generation, namely at least 12.5 % for 2010 and 20% for 2020.

The subsidy scheme in the EEG is fairly complex. Firstly, it distinguishes between different technologies. The highest subsidies are paid to technologies with high costs of generation: Electricity from solar power is subsidized with at least 457 Euro/MWh. Nonetheless, solar power does still play a marginal role in the German electricity generation mix, as the climate in Germany is not favorable for the generation of power from solar energy.

On the other hand, wind power is a technology where the subsidies has triggered significant investments. The subsidy scheme for wind power distinguishes not only between on- and off shore sites but also between production potentials. On-shore wind mills receive a fixed subsidy of 87 Euro/MWh for at least five years after installation. The lower the wind supply at the site, the longer the subsidy applies. After that, the fee is reduced to 55 Euro/MWh. Figure 4 shows both the large increase in RES generation in the recent past as well as expected future growth which is mainly caused by increased generation by wind power.

Figure 6: Electricity Generation from RES in Germany, 2000 - 2030



Source: EWI / Prognos 2005

The costs for the EEG are paid by electricity consumers. For the determination of these costs, all subsidies are aggregated over all RES technologies in a given year. However, the electricity generated by RES also contributes to the electricity system. Hence, the revenue of these sources' generation has to be subtracted to calculate the additional costs in the system brought about by RES. Afterwards, this resulting total additional EEG expenditure is distributed on the total electricity consumption in Germany giving a levy on every MWh of electricity consumed. However, large industrial consumers receive a discount which on the other hand further increases the charge for smaller consumers.

We pointed out that the subsidies of RES plants decrease over time. However, subsidies decrease not only over the life time of a plant but also for new plants depending on the year they are built. For wind power, the subsidy for new installations decreases by 2 % p.a. starting in the year 2006. Nonetheless, in the near future these effects are going to be overcompensated by the steep increase in volumes for RES generation. Furthermore, most studies (e.g. the Royal Academy of Engineering 2004) agree that electricity produced from RES will continue to be more expensive than electricity produced from conventional sources, even if CO_2-certificates increase fuel prices for conventional thermal capacity. Hence, the steep growth in RES generation is going to increase the costs for the EEG subsidies at the same time. For these reasons, the question whether the EEG is an optimal incentive scheme is of highest importance.

For an analysis of the EEG's market design, we first address the question of CO_2-emission reductions. EWI participated in a recent study (EWI et al. 2004) coming to the conclusion that CO_2-emission reductions could be achieved much cheaper by realizing the efficiency gains associated with the replacement of older thermal units with new capacity (mainly highly efficient CCGTs) and upgrading existing thermal units instead of additional RES generation. In addition, unexploited reduction possibilities have been identified on the demand side: sectors such as housing could also reduce CO_2-emissions at lower costs.

Nevertheless, it has been pointed out that CO_2-emission reductions are not the only goal of the EEG. The second goal of the EEG, increasing the security of supply, is difficult to evaluate. However, from the perspective of both security of supply as well as depletion of finite resources, hard coal has to be considered as an alternative.[12] The international energy agency

[12] To be precise, we are not talking about domestic hard coal mining which has to be heavily subsidized but about electricity generation mainly based on imported coal.

(IEA 2004) estimates world coal reserves to last for the next 185 years. In general, these reserves are located in politically relatively stable regions: more than one third of world coal reserves are located in OECD countries. In addition, hard coal is cheap to store (even though it takes significant amounts of space). On the other hand, high pollution, in particular CO_2-emissions, is the main disadvantage associated with electricity generation from hard coal. Another possible source to increase security of supply is nuclear power. While nuclear power is free of CO_2-emissions in addition, this technology suffers from severe disadvantages such as nuclear waste disposal and nuclear accidents. In addition, political acceptance for this technology is currently missing in Germany.

At this point, it becomes apparent that RES are competing with other technologies in the achievement of the aims formulated in the act. While security of supply could be relatively cheaply achieved by increasing the share of coal generation, this is in conflict with the goal of climate protection and the restriction of CO_2-emissions. Nuclear power could achieve both of these goals at the same time; however, at the price of the risks mentioned above. Demand side issues – the reduction of energy consumption in particular – have not been addressed additionally.

To sum up, the introduction of the EEG increased electricity prices considerably and will increase them even more in the future. In principle, these costs can be justified by the political aims of the act. However, we present some evidence, that the related aims could be reached with lower costs to electricity customers – in other words: more efficiently.

2.6 Conclusion

Beginning with a presentation of the development of household electricity prices for the years from 1998 to 2004, we showed that aggregated prices in 2004 are in the same order of magnitude as in 1998 (-3%). However, we argued that such a general consideration might be misleading for two main reasons.

Firstly, the price development shows significant differences among the stages of the value chain. The generation prices experienced a considerable price reduction of about 32% but rose above the level of a competitive market in the years following 2001. Hence, we can draw a mixed conclusion with respect to hypothesis one. Transmission and distribution tariffs declined much less (13%) and seem to increase again since 2004. The hypothesis of abusive network access charges cannot be rejected therefore. The decreases in generation and transmission/distribution prices have been mostly compensated by a significant increase in taxes and subsidies (+56%), which definitely supports hypotheses three and four.

Secondly, we stated that the underlying cost structure - the steep increase in hard coal prices in the generation market for instance - might have changed from 1998 to 2004. While such effects can be expected to level out over time, they can distort the comparison of a small period of observation. For these reasons, we analyzed the different price components at a detailed level.

The main result on the price development for generation is that there is evidence for a paradigm shift from average cost pricing to marginal cost pricing happened after liberalization. However, prices seem to have risen above marginal costs since the end of 2001. Strategic behavior causes a suboptimal dispatch and distorted investment signals. These translate directly into a loss of welfare. Nevertheless, this loss of welfare has to be compared with the loss of welfare which would result in a tighter regulated market.

The access tariffs to the transmission and distribution networks decreased rather slightly or even remained relatively constant. This – regarding the aims of competition policy unsatisfying - result can be attributed to a deficient set-up of the German regulatory scheme. The national NTPA design allowed the network operators to set their network tariffs without the risk of governmental intervention, as long as their Price was within the cheapest 70% of suppliers. In association with an almost perfect transparency on the supply side, such incentive caused cheap suppliers to increase their prices. Though expensive operators reduced their tariffs due to regulatory threat, the German way of electricity network regulation has to be considered to be unsuccessful. We suggested installation of a regulatory agency and the introduction of incentive regulation to increase competition in the retail market and to raise efficiency reserves in network operation.

Finally, we analyzed one of the major subsidies in the German energy market, namely the renewable energy act. After a description of this subsidy's structure, we discussed whether the aims formulated in the act, namely climate protection, increasing the security of supply, restricting the consumption of finite resources and promoting technological progress in RES generation technologies, could be achieved more efficiently by other means. We found that every single aim could indeed be achieved in a more efficient way using other means; however, a deeper analysis is necessary to quantify the act's contribution to all aims simultaneously.

3 Quantifying Market Power in the German Wholesale Electricity Market Using a Dynamic Multi-Regional Dispatch Model

3.1 Introduction

Most of Europe's electricity markets are in the process of liberalization. This process started in Great Britain and the Scandinavian countries. Efforts by the European Union lead to a major movement towards deregulation in continental Europe in the second half of the 1990s.[13] Germany arranged deregulation in 1998 when its new energy law became effective. As a consequence, the first German power exchange in Leipzig started operations in June 2000. Prices on the exchange have increased considerably since June 2000. In particular, monthly base load spot prices (delivery of 1 megawatt (MW) for every hour of the month) varied between 15 and 25 Euros/megawatt hour (MWh) during the year 2000 and most of 2001. In December 2001, the monthly base reached 50 Euros/MWh. On the spot market, where electricity is traded for every hour of the day, prices for the most expensive hours peaked at nearly 1000 Euros/MWh in December. While prices returned to lower levels after December 2001, we show that the spread between marginal costs and prices widened considerably.

Analogous to the discussions around the California crisis (see Borenstein et al. (2002)), two competing hypotheses concerning the cause of these price movements are discussed: the first hypothesis is that high prices in the German electricity market are competitive and purely driven by factors influencing generation costs such as fuel prices, generation of hydro plants, wind power generation and increasing scarcity of generation capacity. The opposing hypothesis states that they are the result of market power. This debate has vital implications for the evaluation of the success of the whole liberalization process in electricity markets. The disadvantages of regulation have to be compared with the disadvantages of market power. Market power, understood as the ability to profitably raise prices above marginal costs, leads to inefficiencies mainly due to restricted output and suboptimal plant dispatch. Market power also shifts consumer benefits from lower prices to generator profits. This chapter contributes to the discussion by deriving a competitive price estimator with a complex dispatch model. A

[13] A milestone towards deregulated electricity markets in the European Union was the EU Directive 96/92/EC which determined common rules for the internal electricity market in the European Union. .

key advantage in our model is the endogenous modeling of intertemporal effects and international power exchange. A comparison of model derived competitive price estimators with observed prices comes to the conclusion that the amount of market power in the German electricity market is significant. We leave the question for further research how market power mitigation could be achieved by improving market design in the German market.

Traditional concentration measures such as the Hirschman-Herfindahl index are rather raw tools for an evaluation of competition and market power in electricity markets.[14] Since information on costs of production and other additional market data are available, they should be used in an analysis of market outcomes. In a perfectly competitive environment, the hourly spot price is given by the marginal costs.[15] Mas-Collel et al. (1995) define market power as "the ability to alter profitably prices away from competitive levels." However, it is impossible to observe true marginal costs. We have to apply a model to estimate marginal costs from observable data. Hence, the difference between marginal cost estimates and prices cannot exclusively be attributed to market power. In addition to market power, differences can be due to a sub-optimal model or uncertainties in the input data.

Borenstein et al. (2002) distinguish two approaches for the analysis of market outcomes. The first analyzes single companies and their bidding behavior. Among others, Wolfram (1998) has conducted such an analysis for the electricity market in England and Wales, and Puller (2001) for California. Bower et al. (2001) applied a bounded rationality model to the German market analyzing the potential for market power in the beginning of the liberalization process. The second approach is at market level. An analysis at market level compares observed prices with estimated marginal costs for the aggregated industry supply function. This approach, e.g. chosen by Borenstein et al. (2002), Wolfram (1999), and Joskow and Kahn (2002), is also followed in this chapter. While this market level perspective is less informative on companies' bidding strategies, the results are far more robust for two reasons. Firstly, a disaggregated approach necessitates the analysis of firms' bidding strategies. Availability of

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[14] See Borenstein and Bushnell (1999) for a discussion of traditional concentration measures and oligopoly models for the analysis of market power in electricity markets.

[15] See Schweppe (1988) for a discussion of marginal costs and spot prices for electricity.

firms' bids differs between countries, and is very low in Germany like in many decentralized markets. Estimating firms' bids would add further uncertainty to the analysis. Secondly, the aggregated approach leaves computational resources for a very detailed analysis of marginal costs. For example, the quantification of marginal costs involves dynamic aspects, which are very difficult to include in a disaggregated model of strategic behavior.

However, the detailed analysis of marginal costs is especially important in the German market. For one, the German power market is highly integrated into the European grid: The available interconnector capacity connecting Germany with its neighboring countries sums up to more than 13 gigawatt (GW), exceeding 15% of highest load. Hence, international power exchanges have to be incorporated in the analysis. In addition, Germany (partly through exchanges with Austria and Switzerland) is significantly influenced by hydro power generation. Optimizing hydro storage generation adds a dynamic component to the problem. Hydro storage plants bid opportunity costs rather than variable costs. Since these plants have a fixed energy budget determined by water inflows, the opportunity costs depend on expected future prices. Bushnell (2003) discusses the intertemporal effects of hydro storage dispatch in a strategic model. Start-up costs are another dynamic issue. They comprise costs for preheating and network synchronization of power plants before production. Start-up costs are price relevant for plants that, for example, shut down during low demand levels at night or at weekends. These costs, however, are most important during peak periods as will be shown later. Since market power is usually also most pronounced during peak periods, it is important to distinguish clearly between the two. Power exchange between regions as well as generation of hydro storage plants and start-up decisions are endogenous to the model presented in this chapter.

We derive system marginal cost estimators using a linear optimization model. The model minimizes total generation costs by simultaneously optimizing plant dispatch in Germany and other European countries. International power exchange is optimized endogenously. Since 72 price realizations per month are distinguished, the dynamic effects of hydro storage plant dispatch and start-up decisions can also be modeled endogenously. System marginal costs are the cost in the system inflicted by a marginal increase in load in a region, taking also into account effects in other regions and other periods.

Comparing the marginal cost estimator with observed market prices at the German power exchange allows a quantification of market power in the market. The most interesting result is that the spread between cost estimators and prices increases over time. One reason for increasing market power is increasing concentration in the market. The eight largest generation companies in Germany merged to only four over the period of observation. Selten (1973) argues that “four are a few and six are many”, indicating that the potential for market power significantly increases when the number of firms is reduced from eight to four. Other studies (e.g. Green and Newbery (1992), Green (1996)) apply supply function equilibria models to power markets. These studies also find a significant potential for market power in markets with few players.

However, it is difficult to pin down a date from which onwards an increase in concentration changes prices. Firstly, at the time a merger is cleared it is not immediately implemented in the organizational structure of a company. It takes an uncertain time span before two merged companies really act as one. Secondly, increasing potential for market power due to increased concentration is not necessarily exploited. Companies have to learn how to exercise market power. The task of reducing output to maximize producer surplus is fairly complex. Both effects are difficult to quantify.

Another factor influencing market power on the spot market are traded volumes on the spot market. Allaz and Vila (1993) show that a higher share of long term contracts can lead to lower spot prices. Bushnell et al. (2003) use empirical data for American electricity markets to show that such vertical arrangements indeed play a role for spot prices. We analyze the development of traded volumes in the spot market and the difference between prices and cost estimators and find that both rise significantly over the time period of our observation.

Hence, our data confirm an increase in the difference between marginal costs and prices over time. We find that average monthly wholesale prices are extremely close to average monthly system marginal cost estimators for the first months (below 2% on average from June 2000 to August 2001). Deviations increase significantly in the later months. The average mark-up from September 2001 to June 2003 is nearly 50%.

Statements about the average degree of market power in a month can be amended by a more detailed analysis, since our model distinguishes 72 different load realizations per month.

However, instead of extensively analyzing single hours, we distinguish periods of high and low demand in every month. The results show that market power is strongest during periods of high demand. Wolfram (1998) finds evidence for the England and Wales market that more inframarginal capacity induces higher bids since more capacity profits from higher prices. In addition, less unused capacity during high demand periods can lower the price elasticity of supply thus raising the potential for strategic bidding. Prices for the peak hours from September 2001 to June 2003 are more than 75% above cost estimators. Much less evidence for market power is detected during low demand periods.

Furthermore, model results allow a quantification of producer surplus. The model determines system marginal costs by determining the cost minimal plant dispatch in every time period. Marginal costs (equaling competitive price estimators), generation by different stations in every period and generation costs can be used to calculate the producer surplus. The analysis shows that producer surplus rises significantly due to the exercise of market power.

To further highlight the implications of our deviation from previous research, we include sensitivity analysis on our crucial methodological improvements. We distinguish model results with and without international power trade, with and without start-up costs as well as with and without varying hydro storage dispatch. In addition, we present sensitivity analyses with respect to thermal power plant availability as this is a major source of uncertainty in the analysis. We present a further sensitivity analysis to quantify the price effect using an average load on a convex supply function. This is achieved by comparing the average of a high and a low demand scenario with our base case.

The chapter is structured as follows. Subchapter 3.2 describes the model developed to estimate the competitive benchmark. In subchapter 3.3, the results from this derivation are explored with regard to spreads, different demand periods and producer surplus. Subchapter 3.4 presents sensitivities with respect to our modeling of power exchange, start up costs, and international power exchange as well as plant availability and demand. Subchapter 3.5 concludes the chapter.

3.2 Modeling Marginal Costs

Electricity markets exhibit unique features which distinguish electricity from nearly all other goods. Electricity is a homogenous product at a certain time on the demand side.[16] Storing electric energy is expensive. Electricity flows are grid-bound. Electricity demand is volatile with pronounced seasonality on a daily, weekly and annual level. Different plant technologies have varying short-run generation costs. These facts lead to large variations in marginal generation costs. Additionally, as capacity has to be sufficient to cover the highest demand levels, there is unused capacity most of the time. These features have to be considered when modeling electricity markets.

Competitive benchmarking studies estimate marginal costs as the intersection of demand and supply. The supply function, called merit order, reflects short run marginal generating costs of different capacity sorted in ascending order. Short run marginal generating costs are usually estimated as the ratio of a generating technology's fuel price and the thermal efficiency of the plant. Sometimes, other variable generating costs are added. However, the correct implementation of this approach is challenging. One key factor to the analysis is that both merit order and demand change over time. In addition, some factors exhibit significant interdependencies over time.

Factors changing on a shorter time horizon are fuel prices, and the availability of plants due to planned revisions and unplanned outages. The production by non-dispatchable power sources such as wind power production and combined heat and power (CHP) generation also varies greatly on an hourly as well as seasonal level. Furthermore, the power exchange between regions can change significantly over time. Generation by hydro run-of-river plants varies according to hydrological conditions. In the longer run, installed capacities also change as old plants shut down and new capacity enters the market. The demand side of the market also varies greatly over time showing different characteristics of seasonality and trends as well as stochastic variations, for example due to changes in the weather. Some factors do not only change but are in addition dependent over time, adding an intertemporal component to the

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[16] One exception is the development of a market for "green electricity". Here, consumers voluntarily buy certificates for electricity produced by renewable energy sources. However, this market is very small.

problem.[17] Hydro storage dispatch as well as start-up decisions of thermal capacity are important examples of intertemporal components.

A significant innovation in our work is the improved modeling of these features, especially international power exchange and intertemporal effects. The studies mentioned above use observed values for these arguments whenever available. However, data on these aspects are often unavailable. In addition, Borenstein et al. (2002) point out that using observed realizations for international power exchange leads to a distorted estimate of market power. Observed exchanges are optimized by market participants based on estimated prices in the market. However, these price signals already incorporate market power. Since we are interested in the competitive counterfactual, it seems advantageous to estimate international power exchange in the model as the result of a cost minimizing plant dispatch.

A similar argument holds for the dispatch of hydro storage and pump storage plants. While it is well known that they generate electricity during peak periods, observed production figures again are already the result of prices potentially including strategic bidding. Hence, the best way to determine hydro storage production is again to include it endogenously in the model. Start-up costs are not included in the existing literature since they are extremely difficult to include in static models due to their dynamic nature. However, they are important for competitive benchmarking studies. One reason is that start-up costs increase prices during periods of high demand but decrease prices during periods of low demand. Hence, neglecting them might identify market power as the result of high prices during peak periods when they are simply an efficient market outcome including the costs to start up new capacity.

3.2.1 Model Structure

The first version of the model was developed by Kreuzberg (2001) who also describes the algebraic structure of the model in the appendix of the cited publication. The model calculates

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[17] Production costs C_t at t do not only depend on output at t but also on past and future production levels: $C_t=C(q_1,\ldots,q_t,\ldots,q_T)$, where $t=1,\ldots,T$ is a time index.

short-run system marginal cost estimators. These comprise fuel costs[18], start-up costs, and opportunity costs for hydro storage plants. In the short term, investment costs as well as costs for labor, and repair and maintenance are sunk. Hence, these costs should not influence plant dispatch; marginal cost estimators should not incorporate them. Short-run system marginal cost estimators are derived by solving a linear programming problem.[19] The objective function is global cost minimization over all model regions. The model becomes particularly appealing through the numerous realistic constraints. Among the more important are:

- Generation has to equal an exogenously given demand at every time everywhere in the network.
- Generation is limited by installed available capacities.
- Power exchange between regions cannot exceed interconnector capacities.
- Dynamic effects to be considered are:
  1. The total generation of hydro storage plants is limited by a monthly energy budget.
  2. Plants may only produce in a given period if they are started up in the same period or have been started in a period of lower demand.

Before we present the accompanying equations in more detail, some remarks should be made on the model's resolution. The first aspect is the model's regional resolution. Plant dispatch is not only optimized for Germany but also for six other European core regions. These core regions besides Germany[20] are France, Belgium, the Netherlands, Austria/Switzerland combined as the Alpine region, Great Britain, and Italy. The size of a region is determined by the grid capacity. If interconnector capacity is abundant over most periods of the year, areas or even countries can be combined to one model region. Power exchange with countries outside the modeled region, i.e. Northern and Central Eastern Europe, is determined exogenously. Regions are abbreviated *reg* in the algebraic model structure.

[18] Fuel costs for nuclear plants comprise the variable components of front end (buying, transporting and processing uranium) as well as back end (treatment and disposal of waste) costs.

[19] This linear programming problem is extensive and involves a total of 400000 equations (with 370000 endogenous variables) to be solved.

[20] Luxembourg is added to the Germany since there are rarely any binding network restrictions between these regions and the largest German generator RWE operates Luxembourg's largest plant.

The next important aspect is the differentiation between different power plants. We do not distinguish single stations but aggregate similar plants in groups. Firstly, we distinguish eight generation technologies (*tech*). These are, for example, nuclear, hard coal or combined cycle gas turbines or open cycle gas turbines. In each technology, we secondly distinguish 10 different five-yearly vintage classes (*v*)[21]. Due to different fuel prices and efficiencies, generation costs for capacity vary between the region the plant is located in, its technology and vintage class.

The time resolution of the model uses 72 different price realizations to construct a month. They represent a working day, a Saturday and a Sunday with 24 hours each. The average weekly and monthly prices are then calculated using appropriate weighting (e.g. 4.8-times working days per week, 1 Saturday and 1.2 Sunday[22]). In the following sets of equations, *lv* labels the load level. The three day types of working day, Saturday and Sunday are referred to with the label *dayt*.

One further remark should be made on the notation. All variables endogenously optimized by the model are in capital letters. All parameters being exogenous input into the model are in small letters.[23]

The model's objective function is given in equation (1). Since the objective is the minimization of total generation costs over all regions and hours, all relevant costs enter the objective function. First of all, relevant costs comprise variable costs for production (VC^P). However, in our model, we also consider start-up costs (VC^{SU}), variable transmission costs (VC^T). All three cost variables on the right side of equation (1) are determined by other equations.

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21 For example, all German hard coal fired capacity built between 1980 and 1984 is in vintage class 1985.

22 Public holidays are treated as Sundays. This gives Sundays additional weight.

23 As the model is implemented in GAMS, we follow the GAMS notation calling everything endogenous a variable and everything exogenous a parameter.

(1) $$C = VC^{P} + VC^{SU} + VC^{T} \rightarrow Min!$$

Equation (2) shows the costs of power production. Production costs comprise specific fuel costs (fc) and other variable costs (o) multiplied by the load output (P^{G}). Specific fuel costs are determined by the ratio of fuel prices (ϕ) and a station's efficiency (η). dur_{dayt} is the number of days each type of day appears to form a week (4.8 for working day, 1 for Saturday and 1.2 for a Sunday).

(2) $$VC^{P} = \sum_{reg}\sum_{tech}\sum_{v}\sum_{dayt}\sum_{lv} P^{G}_{reg,tech,v,dayt,lv} \cdot \left(fc_{reg,tech,v} + o_{reg,tech,v} \right) \cdot dur_{dayt}$$

with

$$fc_{reg,tech,v} = \frac{\phi_{reg,tech}}{\eta_{reg,tech,v}}$$

3.2.2 Modeling Start-up Costs

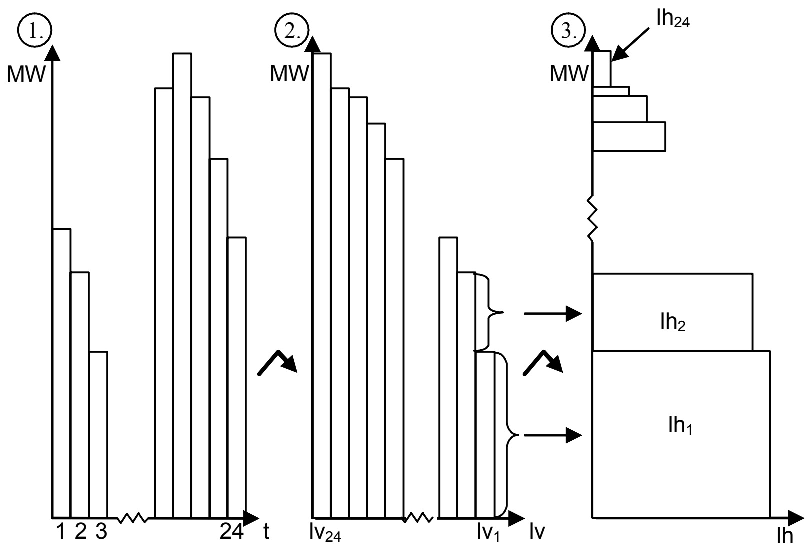
Since the modeling of intertemporal effects is such an important part of our analysis, we will describe their linear approximation in greater detail. A perfect modeling of start-up cost and resulting dispatch decisions would be non-convex. We use a linear simplification to keep the model tractable but still try to capture the important elements of the intertemporal effects.

We achieve this approximation by first transforming the sequential load curve into a load duration curve and then adding a horizontal structure to the problem to map start-up decisions. Figure 7 shows this approach. In step one, the sequential load curve for the 24 hours of a day is shown. The problem with this load structure is to determine which capacity is started-up and hence available for production in which hour. One possibility is to keep the sequential order and sum over all historic start-up and shut-down decisions to determine how much capacity is started up in a certain hour. However, this approach is demanding on computational resources.

Another approach is taken in this chapter by working with load duration curves and introducing a horizontal structure. From step 1 to step 2, the sequential load curve is simply sorted in descending order. Thus, the hourly structure is converted to vertical load levels. The hour with the lowest load is sorted into the first load level (lv_{1}). Using load duration curves instead of chronological load curves is a simplification especially when a load curve has not only a global but also at least one additional local maximum.[24]

In the next step (2 to 3), a horizontal structure is implemented to enable us to determine capacity started up. We distinguish this structure by naming it 'horizontal load level' (*lh*). The crucial difference to the vertical structure is that the lowest load level (lh_1) prevails all 24 hours of the day. lh_2 prevails 23 hours per day and amounts to the load difference between the second-lowest and the lowest load level (see figure).

Figure 7: Intertemporal Structure



The implicit assumption for this approach is that whenever it is efficient to produce with a plant in a certain load level it is also efficient for that plant to produce in all higher load levels as well.[25] We will use the horizontal structure to determine how much capacity is started up at any point in time as well as how long capacity has been standing idle.[26] The amount of capacity that is started up at any point in time (vertical load level lv_x) is the sum over all start-

[24] Kreuzberg (2001) analyzes the simplifications of load duration curves to great detail on p. 61 ff.

[25] This assumption is correct as long as the load structure is single-peaked (as it is the case during the summer months). However, it does not necessarily hold when the load structure has two (local) maxima.

[26] Idle times are important as start-up costs are below cold start costs when the plant is still warm.

ups in horizontal load level lh_y with $y \leq x$. The idle time is determined by the horizontal load level the plant was started up. If the plant was started in lh_1, it has not been standing idle at all since it is running all 24 hours of the day. In general, a plant started up in lh_y is assumed to have been idle for *y-1* hours – all those hours where the load was lower. The crucial advantage is that start-up costs are paid once in the horizontal load level the plant is started up but the plant is available for production without further start-up costs in all periods with higher demand.

Using the concept of the horizontal load structure facilitates the interpretation of the start-up cost related equations. The start-up costs VC^{SU} were introduced as part of the objective function (1). They are the sum of all start-up costs in the whole system, i.e. total start-up costs of all stations started up, in all regions (*reg*), all technologies (*tech*), all vintages (*v*), during each type of day (*dayt*), and for each load level (*lh*). CAP^{SU} is the capacity started up in a certain load level and *sc* are station and load level specific start-up costs of this capacity. Start-up costs (*sc*) comprise both attrition costs and fuel costs. Start-up costs decrease if a generation set was only shut down for a short period of time and did not cool down entirely. If *s* are the start up costs of a cold generation set, then (4) gives the start-up costs after a stop of length *t,* with *T* the characteristic time constant of the plant.:

(3) $$VC^{SU} = \sum_{reg}\sum_{tech}\sum_{v}\sum_{dayt}\sum_{lh} CAP^{SU}_{reg,tech,v,dayt,lh} \cdot sc_{tech,v,dayt,lh} \cdot dur_{dayt}$$

(4) $$sc_{tech,v,dayt,lh} = s_{tech,v} \cdot \left(1 - e^{-\left(t^{nl}_{dayt,lh} / \mathrm{T}_{reg,tech,v}\right)}\right)$$

As part of the objective function VC^{SU} is minimized in the model. The minimization is subject to the following constraints. Firstly, generation cannot exceed the amount of capacity started up:

(5) $$P^{G}_{reg,tech,v,dayt,lv} \leq \sum_{lh|lh \leq lv} CAP^{SU}_{reg,tech,v,dayt,lh}$$

Furthermore, not all installed capacity can be used. Equation (6) states that the variable CAP^{SU} is bounded above by the available share (α^G) of installed generation capacity (χ^G). Installed capacity can be unavailable for two reasons. Firstly, stochastic outages restrict availability of installed capacity. Secondly, plants have to shut down for repair and maintenance. We combine maintenance related and stochastic outages in an exogenous factor α^G. The determination of this parameter is described in the data section in appendix A.

(6) $$\sum_{lh} CAP^{SU}_{reg,tech,v,dayt,lh} \leq \alpha^{G}_{reg,tech,v} \cdot \chi^{G}_{reg,tech,v}$$

Another important restriction is the minimum load constraint in equation (7). This equation states that there is a lower limit (π^{min}) for plants operated in partial load modus. Usually, utilization of capacity started up is not allowed to fall below 60%.

(7) $$P^{G}_{reg,tech,v,dayt,lv} \geq \pi^{min}_{tech,v} \cdot \sum_{lh} CAP^{SU}_{reg,tech,v,dayt,lh}$$

3.2.3 Modeling Hydro Storage Dispatch

Pump storage plants are optimized in a weekly cycle. An additional constraint contains a maximum load factor per day which is included to capture limited reservoir sizes. Equation (8) determines the storing of electricity in the form of pumped water. An energy budget $Q^{max,PS}$ (left side) is stored by consuming electricity for pumping (right side). Note that both sides of this equation are endogenous variables.

(8) $$Q^{\max,PS}_{reg,v} \leq \sum_{dayt}\sum_{lv} P^{P}_{reg,v,dayt,lv} \cdot \eta_{reg,"hyd\_PS",v} \cdot dur_{dayt}$$

Equation (9) determines the use of the energy stored in $Q^{max,PS}$:

(9) $$\sum_{dayt}\sum_{lv} P^{G}_{reg,tech,v,dayt,lv} \cdot dur_{dayt} \leq Q^{\max,PS}_{reg,v}$$

Finally, equation (10) states a general fuel constraint for plants. θ, the fuel budget, is usually not set to binding values except for hydro storage plants. In some cases it might be required to set a binding value for lignite if the pit capacity could not provide the amount of lignite the station would burn in the unconstraint dispatch.

(10) $$\sum_{dayt}\sum_{lv}\frac{P^{G}_{reg,tech,v,dayt,lv}}{\eta_{reg,tech,v}}\cdot dur_{dayt}\le\theta^{\max}_{reg,tech}$$

3.2.4 Modeling International Power Exchange

Equation (11) shows the costs of power transmission between model regions. These costs comprise the national grid entry costs (production P^G times the national entry rate $\tau_{reg,reg}$) and the costs of cross-border exchange (P^T times the cross-border tariff rate from region r to region reg, $\tau_{r,reg}$).

(11) $$VC^{T}=\sum_{reg}\sum_{dayt}\sum_{lv}\left(\sum_{r}P^{T}_{r,reg,dayt,lv}\cdot\tau_{r,reg,lv}+\sum_{tech}\sum_{v}P^{G}_{reg,tech,v,dayt,lv}\cdot\tau_{reg,reg,lv}\right)$$

It has been pointed out that international power exchanges are assumed to follow contract paths. This will be used in equation (13). The only limiting factors for power flows between regions are available net transfer capacities (NTC). These NTC values (χ^T) can be adjusted varying their availability (α^T) as shown in equation (12). The association of European Transmission System Operators (ETSO) publishes bilateral and multilateral net transfer capacities (NTCs) for power exchange between countries which are used in the model as capacity limits.

(12) $$P^{T}_{reg,r,dayt,lv}\le\alpha^{T}_{reg,r,dayt,lv}\cdot\chi^{T}_{reg,r}$$

Power exchange between model regions and non-modeled satellite regions (Eastern Europe, Northern Europe, and Spain) are considered being exogenous based on available statistics. Satellite regions are referred to with *satreg*, the exogenous exchange parameter for exchange from a satellite region to a model region is called $psat^{ex}_{satreg,reg}$.

3.2.5 Modeling the Demand Constraint

The demand constraint captures the impact of international power exchange as well as storage and pump storage generation (equation (13)). Load (l) in each region and each hour has to be covered by generation and imports. Load (l) is an exogenous parameter assumed to be price inelastic.[27] Domestic generation, P^G, minus electricity consumption of domestic pump storage stations, P^P is domestic net production. The power exchange balance of imports and exports ($P^T_{r,reg}$ $+psat^{ex}_{satreg,reg}$ $-P_{reg,r}$) is the second source to cover demand. Imports from model regions are reduced for transmission losses (υ^T). Transmission losses amount to approximately 10% per 1000 km of average transportation distance (δ) independent of the utilization level of the interconnectors.

$$\begin{aligned} &\sum_{tech}\sum_{v} P^G_{reg,tech,v,dayt,lv} - \sum_{v} P^P_{reg,v,dayt,lv} \\ \textbf{(13)}\quad &+\sum_{r}\left(1-\upsilon^T_{r,reg}\right)\cdot P^T_{r,reg,dayt,lv} - P^T_{reg,r,dayt,lv} + \sum_{satreg} psat^{ex}_{satreg,reg,dayt,lv} - \varepsilon_{reg,satreg,dayt,lv} \\ &\geq l_{dayt,lv,reg} \end{aligned}$$

$$\text{with}\quad \upsilon^T_{reg,r} = \frac{0.1}{1000}\cdot\delta_{reg,r}$$

System marginal costs – our competitive benchmark – are the marginal ('shadow price' or dual variable) of this demand restriction. They can be directly derived from the optimization problem. Loosely speaking, they answer the question how total costs (the objective variable) in the whole system (over all time periods and in all regions) would change if the demand in hour t (l_t) was increased by one unit.

3.3 Empirical Results

In this subchapter, we will present the results from the application of the model to the German power market. Following a very brief presentation of some disaggregated results for the three characteristic days per month distinguished in the model, aggregated monthly average prices and costs will be analyzed. Afterwards, high demand and low demand periods will be

[27] Inelastic demand has the problem that the market might not clear if there is insufficient capacity. This is solved in the model by adding a 'value of lost load' (VOLL) technology with variable generation costs of 2000 Euro/MWh. However, demand can be served with regular technologies at all times in the section on empirical results. This changes in the sensitivity analyses without international exchange and hydro storage flexibility where VOLL sets the price occasionally (see subchapter 3.4).

analyzed separately. This is done to test the hypothesis that market power is strongest during high demand periods. In the last part of this subchapter, we will analyze changes in producer surplus due to the deviation of prices from marginal costs.

The German electricity market is the largest in Europe. Total net consumption summed up to 532 TWh in 2000. Total installed net generating capacity at the beginning of the year 2000 amounted to 116 GW (25% hard coal, 22% gas, 18% nuclear power, 18% lignite, 8% hydro power, 5% wind, 4% oil and others). The highest share of the German electricity market is covered by long term contracts. The spot market for electricity comprises an over-the-counter (OTC) and an exchange-based branch. The amount of electricity traded on the spot market increased continuously during our period of observation. We will show later that the largest share of the spot market is traded on the power exchange. We therefore compare average spot prices from the power exchange[28] with our cost estimators, assuming a working arbitrage between the different spot markets.

The approach in this chapter overestimates the capabilities of market participants resulting in a downward bias of system marginal costs: The model assumes perfect foresight concerning fuel prices, load, electricity generation from wind, and other sources, and excludes any market frictions. The market is assumed to be free of arbitrage opportunities. These market frictions raise prices above our competitive benchmark even in the absence of market power. However, the effect should decrease over time as market participants learn to operate more efficiently. This is in contrast to our results which exhibit widening spreads between prices and competitive benchmark.

In addition, information about supply and demand data is incomplete. It is therefore not possible to replicate exactly the situation seen by the power plant operators. Data uncertainty may lead to an overestimate or underestimate of marginal costs. We will perform sensitivity analyses in subchapter 3.4 and give a description of input data in appendix A to develop a feeling for both model and data accurateness.

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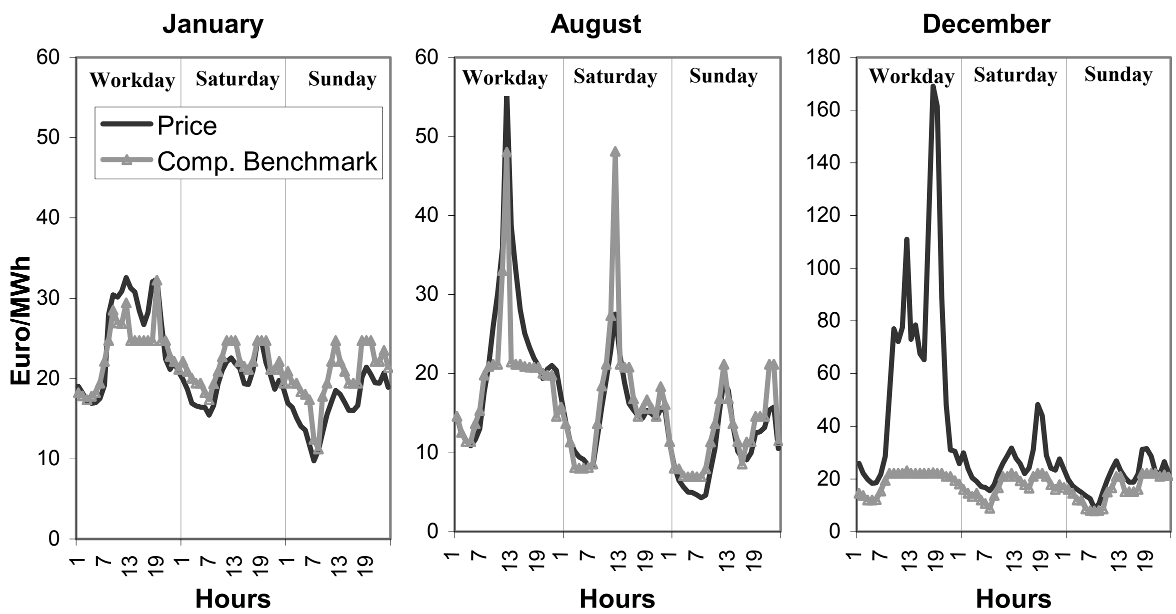
[28] From August 2000 to July 2002 two separate power exchanges were operating in Germany. We use the volume weighted average price of the two exchanges as market price in this period.

3.3.1 Presentation of Marginal Costs and Prices

Figure 8 gives examples of hourly price curves for Germany. Each diagram contains 24 hours for a typical working day, Saturday and Sunday. The EEX prices are obtained by averaging realizations of all days belonging to the relevant type of day (working days, Saturdays or Sundays plus public holidays) at a certain hour in the month. The exchange’s price realizations are compared with the model’s estimated competitive benchmarks. It can be seen that the model reflects the structure of the EEX prices fairly well during January and August 2001. Prices and SMC estimators differ greatly during December 2001. Prices are two or three times as high as cost estimates especially during high price periods.

Figure 8: Hourly Average Prices and SMC Estimators, Germany 2001



To allow a formal comparison of the price differences the hourly realizations are aggregated into a monthly base, peak and off-peak realization. A monthly base realization is calculated by averaging all hourly price realizations at the exchange. Model estimates are time-weighted averages of the 72 realizations per month.

Figure 9: Monthly Averages – Price and Cost Estimators

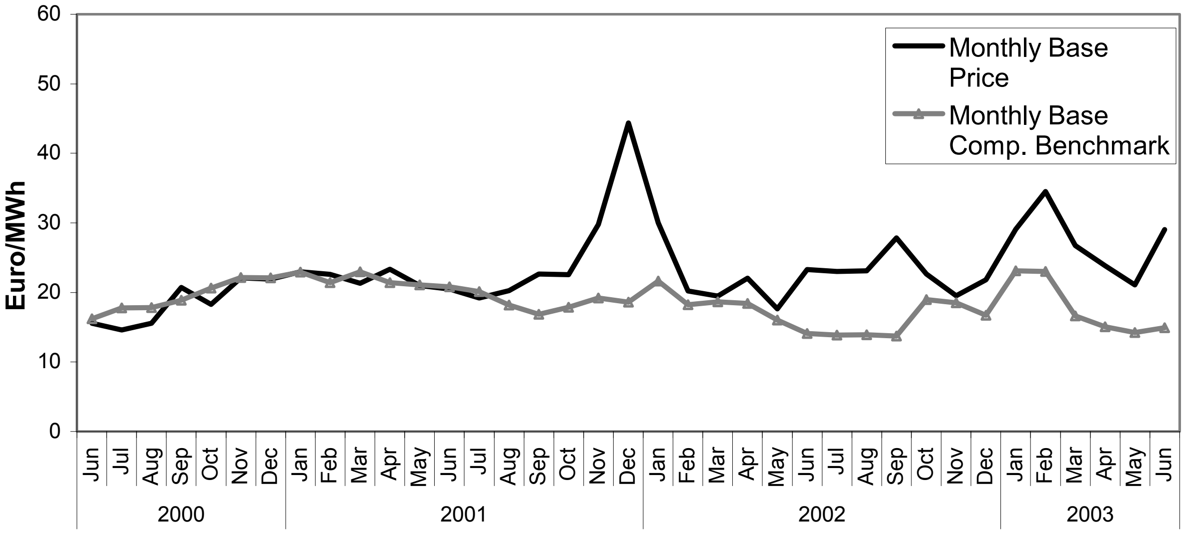


Figure 9 visualizes a key observation in this chapter. The development of the difference between model estimates and market prices over time is striking. A simple graphical analysis shows that the coherence between costs and prices is much stronger at the beginning of the observation period.

To get a better feeling for the development of the spread between prices and competitive costs, we subdivide the observation period in two sub-periods. In a first period from June 2000 to August 2001 there is no evidence for market power.[29] The ratio of monthly EEX prices to average monthly marginal cost is nearly 0.99. Hence, prices are even slightly below estimated marginal costs. Short-run marginal costs should be a lower bound for prices. As was pointed out before, both suboptimal bids by market participants and uncertainties in model input data do possibly lead to SMC estimates above prices. For the period after the structural break, the ratio of prices to costs increases to 1.45. While marginal costs fell from the first to the second period, prices increased significantly. This caused the strong increase in differences between prices and costs.

[29] The length of this sub-period is suggested by a QLR-test for the most likely statistical date for a structural break in the price-cost margins.

How can this significant increase in price-cost-margins over time be explained? Several factors influencing competition have changed during our period of observation:

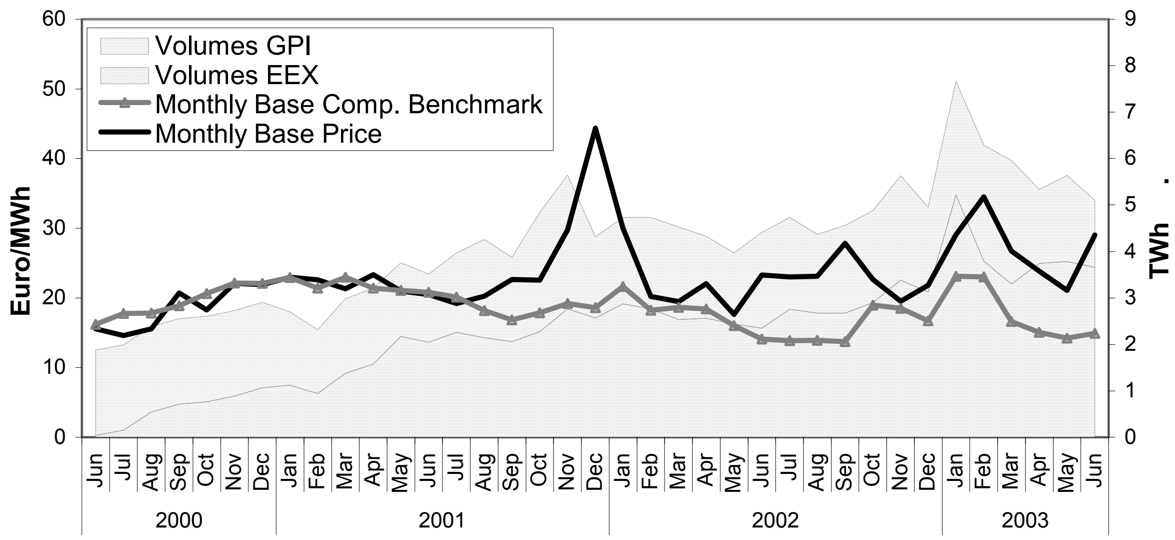
- concentration in the market increased,
- competition was reduced due to a load increase combined with capacity reductions,
- the share of energy sold on longer-term contractual arrangements decreased as spot market trading increased.

When the German electricity market was liberalized, eight major integrated generation companies dominated the market. During the years 2000 and 2001, mergers and acquisitions reduced this number to four. RWE and VEW merged but kept the name RWE. Preussen Elektra and Bayernwerk merged to E.ON. Swedish Vattenfall first bought HEW. Afterwards, HEW, VEAG, and BEWAG merged to form Vattenfall Europe. In addition, French EdF bought a major share of the south-western player EnBW. At the same time, the amount of installed thermal generating capacity was reduced by about four GW in the years from 2000 to 2003. Shut downs or conservations of more than 10 GW have not been balanced by additions of about 6 GW. However, such effects do not directly translate into strategic bidding and prices above system marginal costs. The reason is that a potential for strategic behavior is not necessarily exploited. Firstly, a merger has to be implemented in the organizational structure of a company. Secondly, companies have to learn how to exploit the potential for strategic bidding. Thirdly, implicit threats of regulatory interference can keep prices down. Hence, it is out of the question that the potential for strategic bidding increased in the German market. Gathering data on these factors and using them as explanatory variables is left for further research.

Another line of reasoning was started by Allaz and Vila in 1993. They analyze optimal bidding strategies for strategic players optimizing their supply on both a spot and a forward market under Cournot competition. They argue that in equilibrium firms' competition in the forward market increases their output commitments thus bringing prices closer to competitive levels. It is very plausible that strategic behavior on the spot market is less attractive for firms if they have already sold their output under long-term contracts. While this argument is somewhat static in nature, Bushnell et al. find empirical evidence for the US that a higher forward contract coverage does – ceteris paribus – lead to lower spot prices. For this reason, we show prices, competitive benchmarks and the amount of electricity traded on the German spot market in Figure 10.[30]

Initially one might not expect a link between Enron's bankruptcy and the German electricity prices as Enron did hardly own plants in Germany[31], international flows did not change significantly, and demand was not altered. However, Enron had large contracted positions with both the supply and the demand side. They had to be replaced and the GPI data indeed shows a 17% increase in the volumes of spot market trading for November 2001 (Figure 10). These increased volumes in the spot market raise the incentive for strategic players to increase prices. While this might help to explain the relatively high spread between prices and competitive benchmark in November 2001, it does not answer all questions for December 2001, were prices reached all-time records of up to 2000 Euro/MWh.

Figure 10: Relation between Traded Volumes on the German Spot Market (TWh, right axis), Prices, and Cost Estimators (Euro/MWh, left axis)



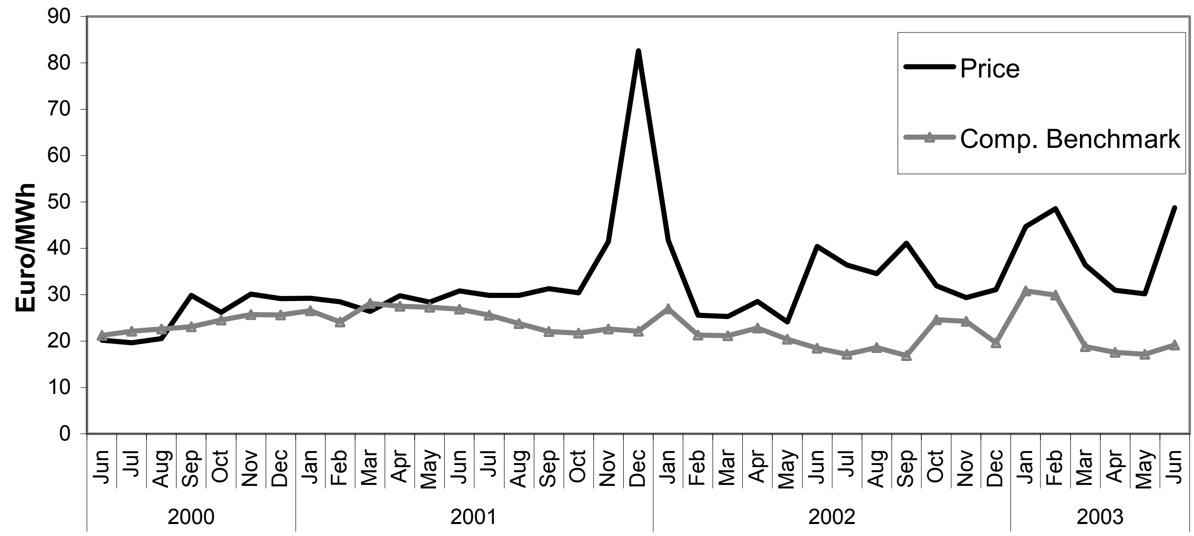
[30] GPI stands for 'German Power Index'. This index is computed by DowJones based on voluntary declarations of agreed deals by market participants. Hence, total traded volumes in the spot market might be higher than those in the figure. In addition, we estimated GPI data for the year 2000 as being equal to the average of the year 2001.

[31] The single exception was a 50% share in a 106 MW_{net} CHP plant.

3.3.2 Comparison of High and Low Demand Periods

It is often argued that market power is higher during high demand periods than during low demand periods. Both a higher amount of inframarginal capacity profiting from higher prices and the amount of free capacity are intuitive reasons for this. The higher price-cost margin for peak periods in Figure 11 relative to off-peak periods in Figure 12 supports this hypothesis.[32] The ratio from prices to costs increases from 1.09 in first period to 1.75 in the second period.

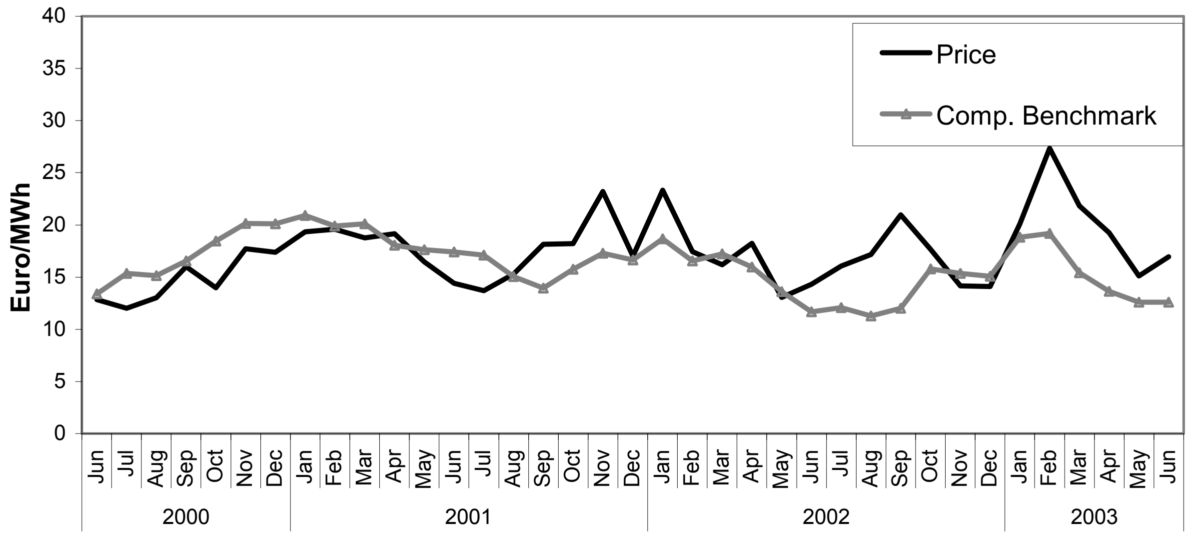
Figure 11: Monthly Averages Peak Hours– Prices and Cost Estimators



The same type of analysis for the off-peak periods shows a very different result. However, Figure 12 shows that the deviation between marginal costs and prices is much smaller. The ratio of prices to cost estimators is 0.9 in the first period and rises to 1.21 in the second period.

32 The peak period comprises Monday to Friday from 8 a.m. to 8 p.m. (including public holidays). All other hours are contained in off-peak realizations.

Figure 12: Monthly Averages Off-Peak Hours – Prices and Cost Estimators



3.3.3 Producer Surplus

How do higher prices translate into higher profits for the electricity supply industry? Producer surplus is determined by hours of generation, production costs and prices. In the competitive benchmarking case, all three are determined by the model. The model optimizes plant dispatch by minimizing production costs. These data can be used to determine producer surplus for the capacity in the model by multiplying generation with the competitive price estimator and subtracting variable generation costs.[33] Estimated producer surplus earned in the competitive counterfactual can be compared with contribution margins earned by selling in the EEX spot market. Here we assume the simulated plant dispatch and production costs but use EEX spot prices instead of competitive estimators as prices. Most likely, plant dispatch under strategic behavior is not cost minimal, and production costs would increase compared to the competitive scenario.

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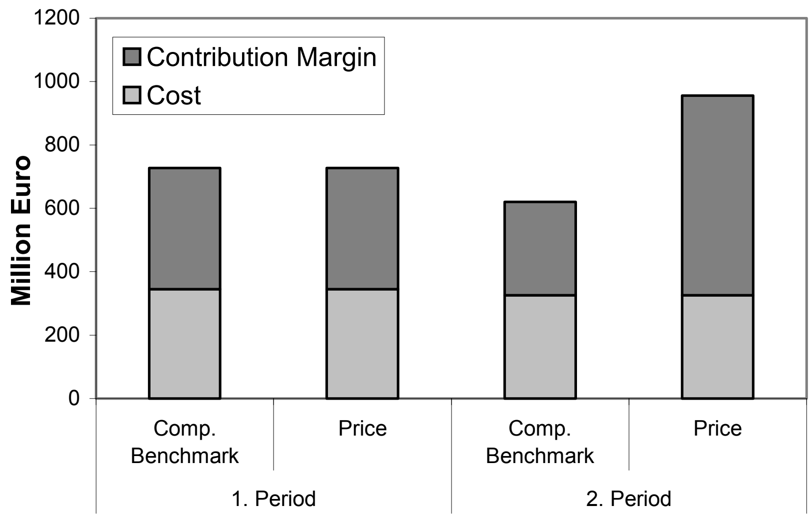
[33] Non-dispatchable generation is not considered in the following calculation of revenues since its dispatch is not optimized by the model. This is because data on the generation cost of combined production of heat and power plants is difficult to obtain.

A major share of capacity is bound by long-term contracts and is thus not directly influenced by higher spot prices. Hence, the results presented in this subchapter can be seen as an upper limit for producer surplus under strategic behavior.

We do not perform a comparison of contribution margins for all 37 months but instead subdivide the period of observation in two (June 2000 to August 2001 and September 2001 to June 2003). Since these two periods do not have the same length, a comparison of absolute figures is misleading. For that reason, monthly average costs and revenues are calculated in both periods. Figure 13 contains monthly average revenues and costs for both periods.

Figure 13: Monthly Average Revenue, Costs, and Producer Surplus



Revenues for the first period are very similar for the competitive benchmark and realized market prices. Monthly average revenues for all modeled capacity in Germany amount to about 727 million Euros in both cases. Monthly average generation costs are defined to be the same in both cases. They amount to 345 million Euros. Since producer surplus is the difference of revenues and variable costs, they are also the same and amount to a monthly figure of 382 million Euros. At this point it is interesting to note that even in a competitive environment, inframarginal plants earn significant profit contributions.

Average monthly revenues for the second period are 620 million Euros using the competitive price estimator and 956 million Euros for EEX prices. Producer surplus increases from 294 million Euros using competitive price estimates to 630 million Euros using market prices. This is an average monthly difference in producer surplus of 336 million Euros. It is interesting to note that the extra profit gained in December 2001 was 1.4 billion Euros. While observed prices are 47% above SMC estimators for the second period, producer surplus calculated using EEX prices are even 114% above producer surplus under SMC. The reason is that marginal costs cover both production costs and producer surplus while the increase in prices due to market power exclusively raises producer surplus. In addition, it should be noted that competitive estimates of revenues, costs, and producer surplus is all lower in the second period than in the first. This is mainly caused by lower prices for hard coal and gas in the second period leading to lower price estimators. Lower prices lead to lower revenues especially for inframarginal capacity such as nuclear, lignite and hydro generation. Hence, there seems to be no reason other than strategic behavior for the observed price increase in the second period.

If prices above long run marginal costs of new capacity trigger new market entry by non-strategic players, strategic prices should not significantly exceed long run marginal costs. Analyzing EEX price data for the year 2003, we find that prices are still slightly below long run marginal costs of a new CCGT plant.[34]

3.4 Sensitivity Analysis

The model structure and the quality of input data are reasons besides market power why prices deviate from model-estimated competitive benchmarks. We test how robust the results are to changes in the model assumptions.

In the first part of this subchapter, we quantify the impact brought about by our improved modeling of international power exchange and intertemporal effects. This also gives a feeling for the effect of changes in the model structure. In the second part of this subchapter, we further analyze the robustness of our results. We achieve this by varying the crucial but unobserved input parameter plant availability. Furthermore, we analyze the effect of using average load curves in the model, another methodological aspect.

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[34] Long run marginal costs include labor costs, repair and maintenance costs, and annualized investment costs in addition to short run cost.

3.4.1 Quantification of Model Improvements

We vary the three key factors international power exchange, start-up costs and hydro storage dispatch to test the sensitivity of resulting dispatch and prices. The efficient benchmark is in all three cases the endogenous optimization of the variable. To compare these results with a clear cut benchmark, we chose rather simple alternatives. In the case of international power exchange, we set German power exchange equal to zero in all periods.[35] The scenarios without start-up costs abstract from all start-up costs fixing them equal to zero. In the scenarios with inflexible hydro storage production, we do not set the generation of storage plants to zero but instead assume that the historic available hydro energy inflow is produced at a flat level during all hours of the year. In effect, this means assuming that all hydro energy is generated by run-of-river plants and not reacting on price signals. Pump storage generation is set to zero.[36]

We calculate all possible combinations of these three factors thus computing eight different scenarios. The scenario which optimizes all three variables endogenously is equivalent to the base case analyzed to great extend in subchapter 3.3. The scenario without endogenously optimizing any of these variables represents a static merit order analysis. The results are presented in Table 4 (aspects endogenously optimized are indicated with a ‘yes’).

We show the results for the two sub-periods mentioned in subchapter 3.3 (June 2000 to August 2001 and September 2001 to June 2003). In each sub-period we distinguish the base price covering all hours of the period, the peak price covering only the hours from 8 a.m. to 8 p.m. on working days. The off-peak hours again cover all hours except peak hours. ‘Max’ is the average of the most expensive hour in each month over all months in the sub-period.

Analyzing selected results, we want to stress again that observed market prices are fairly close to the base scenario (yes, yes, yes) during the first sub-period but different during the second.

---

[35] This is very close to the annual average as netted power exchange over the year is very small in Germany (e.g. about 1 TWh in both 2001 and 2002). However, both aggregated imports and exports amount to about 45 TWh (UCTE statistical yearbook 2002).

[36] In addition, we assume that CHP and wind generation are constant over the year. This is done to generate a setting comparable to a simple merit order analysis if all three aspects are fixed to the historic average.

Furthermore, it is interesting to compare the base scenario with the three scenarios where just one argument is not optimized endogenously (nyy, yny, yyn). Comparing the base scenario (yyy) and the case without international power exchange (nyy), we find that the base price increases significantly. This highlights the importance of international power exchange for the German electricity system – and the importance of modeling this variable correctly. Furthermore, we find that the effect is exclusively coming from the peak periods when Germany is profiting from cheap imports – a large share of which is hydro storage production from the Alpine countries and Northern Europe.

Looking at the effect of start-up costs, we compare yyy with yny. We find that the base price is nearly unchanged, but peak prices (and especially the maximum) are increased by start-up costs and off-peak prices decreased. Lucas and Taylor (1994) discuss start-up costs and their influence on marginal costs. They give the intuition that a load increase during most periods can be served by an earlier start-up (or later shut-down) of a plant that has to be started up anyway. The exception is the period with highest load for thermal plants. In this period, a load increase has to be served by otherwise unused capacity. Hence, start-up costs are cost relevant. During the lowest demand periods, the opposite can be observed. During the lowest demand period, a load increase increases variable operating costs but saves a start-up in the next period since more capacity can be operated without interruption. While start-up costs hardly change the base price, it is nonetheless advantageous to include them in a model. Otherwise, high prices during peak periods might be wrongly attributed to market power. This is especially important if only parts of the observation period are analyzed, for example high price periods.

Furthermore, we compare the results of a flat hydro storage dispatch (yyn) with the base case. This comparison is interesting as it shows the effect of a redirection of hydro energy production. We do not change the total amount of hydro energy in the system. We see that the effect on the base price is noticeable especially in the second period. This is partly caused by the reduction of excess capacity which makes thermal production in the high demand periods more expensive (and hence increases the value of hydro production in these hours). In general, we find that peak prices are greatly reduced by the flexibility of hydro while off-peak prices are increased as hydro energy shifts from off-peak to peak periods when the dispatch is flexible over time.

While we leave the interpretation of the rest of the table to the reader, the results for the second sub-period in the two scenarios with neither international exchange nor flexible hydro storage dispatch (nyn and nnn) need explanation. Under these circumstances, capacity inside Germany is not sufficient to cover load. Hence, prices during the highest demand periods in some months are set by the value of lost load.[37] These tight situations of supply and demand lead to very high cost maxima raising both base and peak cost estimators. However, the fact that load cannot be served without cross-border trade and hydro flexibility during these periods seems more interesting in the context of the current analysis than the absolute height of resulting costs.

Table 4: Cost Estimates Depending on Model Set Up [Euro/MWh]

			Period 1: Jun 2000 to Aug 2001				Period 2: Sep 2001 to Jun 2003			
			Base	Peak	Off Peak	Max	Base	Peak	Off Peak	Max
Market Price			20.00	27.24	15.96	39.71	25.20	37.07	18.68	66.15
Trade	Start-Up Cost	Hydro flexible								
yes	yes	yes	20.30	25.01	17.68	47.18	17.38	21.57	15.05	38.50
no	yes	yes	24.18	34.85	18.26	79.14	22.02	33.07	15.86	81.47
yes	no	yes	20.43	22.96	18.98	24.79	17.50	19.97	16.09	22.19
yes	yes	no	21.26	30.03	16.36	54.89	20.84	31.48	14.90	54.04
no	no	yes	23.93	31.00	19.93	52.58	21.66	29.43	17.26	60.16
no	yes	no	24.49	37.64	17.15	78.56	66.71	151.33	19.59	252.62
yes	no	no	21.14	27.16	17.71	32.91	20.46	28.37	16.00	33.83
no	no	no	23.55	33.64	17.84	47.52	60.80	134.00	19.95	226.38

3.4.2 Sensitivity Analysis on Thermal Plant Availability and Average Load

In the first scenario in this subchapter, we analyze one of the main sources for uncertainty in the model data, namely the availability of thermal generation capacity. While data on a monthly level is available for nuclear stations in all countries, the only German data currently available for regular thermal power stations' availability is historic averages before our period of observation (see appendix A). We reduce the availability of all German capacity by an additional 10 % beyond historic averages used in the base scenario. The second scenario

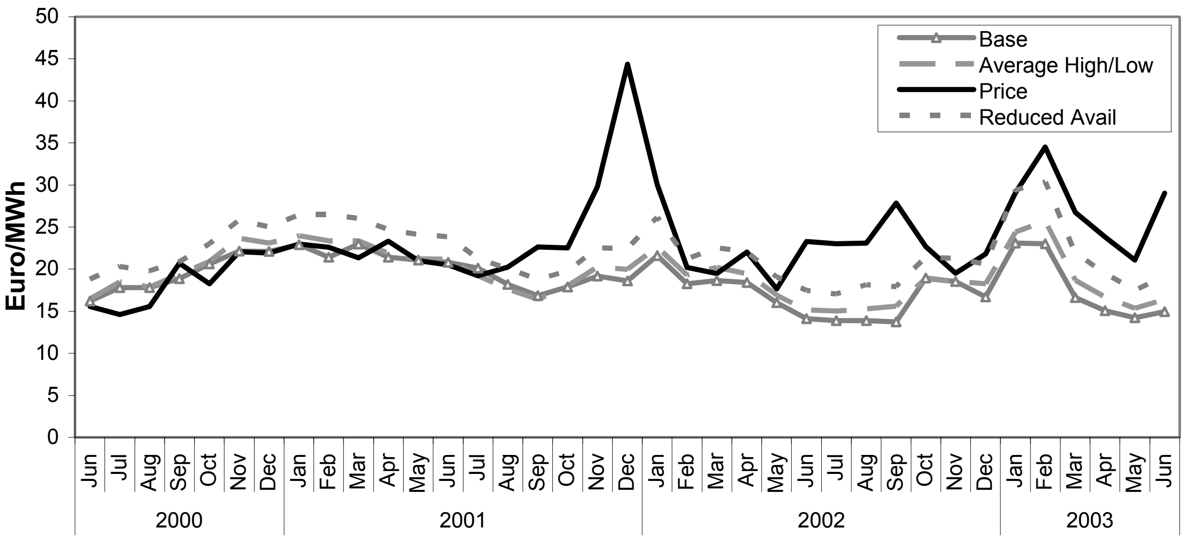
[37] We assumed a value of lost load (VOLL) of 2000 Euro/MWh. VOLL is needed in these two scenarios only; there is no capacity shortage in the system in any of the other scenarios.

evaluates the error made by optimizing three representative days per month (with 72 different hours distinguished) instead of 30 days (with 720 hours). If the supply function is convex, optimizing dispatch for average load curves underestimates system marginal costs. We quantify this effect by looking at the average of a high demand scenario (German demand increased by 10%) and a low demand scenario (German demand reduced by 10%).

The results ob both scenarios are presented in Figure 14. Reducing the availability of German capacity leads to a significant price increase. However, the price increase is still below observed prices in the second period. On the other hand, the competitive benchmark is now persistently above observed prices in the first period. Hence, if wrong assumptions on plant availability should be the reason for the difference between our competitive benchmark and prices, plant availability must have been much lower in the second period of observation than in the first.

While plant availability has a rather large effect on marginal costs, the effect of convexities in the supply function seems to be a minor aspect. We find that the average of a high and a low demand scenario is above the base case for nearly all months. However, the magnitude of the effect seems to be negligible. Further analysis not included in Figure 14 reveals that the scenario with a 10% demand increase is very similar to the case with the 10% reduction in plant availability.

Figure 14: Monthly Averages – Sensitivity Analysis



3.5 Conclusion

This chapter analyzes the extent of market power in the German wholesale electricity market. In contrast to previous competitive benchmarking studies, we include dynamic aspects and international power exchange when calculating the benchmark. The linear optimization model we present incorporates these aspects by simultaneously optimizing 72 hours instead of just one point in time. We use this model to quantify the market power by comparing a marginal-cost-based competitive price estimator with observed power prices on the electricity spot market. Strategic behavior is identified as the main reason for the difference between marginal costs and prices.

The methodology presented in this article can be applied to any power market. The method is well suited for markets with a large share of hydro storage capacity as hydro storage dispatch decisions are intertemporal. However, it is also suited for markets dominated by thermal generation capacity as it captures important features of intertemporal start-up costs. It is particularly appealing in markets with a high importance of interregional power exchange.

We apply the model to the German power market. There is no evidence for market power at the beginning of our observation period. In the months from June 2000 to August 2001, monthly average prices are nearly identical to marginal cost estimates. However, there is strong evidence of market power in the later months. In the period from September 2001 to June 2003, prices are on average nearly 50% above estimated costs. Mostly, these price differences lie in periods of high demand. In the second period, prices are 75% higher than cost estimators for these high demand phases. Producer surplus based on EEX prices are also calculated: in the second period, they are more than double compared to the competitive benchmark.

Increased concentration was named as one potential reason for the evidenced increase in producer surplus and market power. Another potential reason is learning which unfortunately is not easily measured and thus also difficult to quantify. However, electricity spot market auctions repeated on a daily basis will no doubt have led to more sophisticated bidding strategies. Furthermore, increased spot market volumes may raise the incentive to employ strategic behavior as it becomes more attractive. We find that both traded volumes on the spot market as well as strategic mark-ups increase over time.

Regardless of the origins of market power, the careful analysis of supply and demand situations is absolutely crucial for an understanding of electricity markets and possibly resulting market power. Even in perfectly competitive markets, we can expect strong variation in prices over time and price spikes during extremely tight situations of supply and demand. In addition, due to differences on both the supply and the demand side, competitive prices have to be different for different regions as long as they are not linked through sufficient interconnectors. Hence, high prices alone are no proof of market power and, subsequently, associated inefficiencies and rent shiftings. Most empirical studies determine marginal cost estimators by simply moving hourly load (demand) over a static supply curve. However, the supply functions of different periods are interdependent and they are not constant over time. Non-dispatchable energy sources such as wind power and combined heat and power plants vary from hour to hour and influence the time-specific supply function significantly. International power exchange, start-up costs, hydro storage plants' opportunity costs and provision of reserve power are important and were thus modeled endogenously in this chapter.

By quantifying the degree of market power in the market, the chapter sheds light on the discussion of recent price rises in the German electricity industry. Strategic bidding by generating companies seems to be the primary source for price increases in the German market. Changes in fuel prices, capacities and demand play a minor role. Average marginal cost estimators during the second period were below the average of the first period while spot prices in the market were much higher. This result is important for the discussion of the success of market liberalization and deregulation. Market power is one of the key problems in deregulated markets. Potential changes in regulation and market design have to be considered if the degree of market power is too large. However, the quantification of "too large" is difficult. The disadvantages of deregulated markets have to be compared with the disadvantages of a tighter regulation. Several potential measures to mitigate market power are discussed in the literature. They show greatly varying degrees of regulatory interference. Among others, the literature discusses measures to increase the price elasticity of demand and to expand forward contract volumes, the implementation of price caps, the promotion of additional interconnector capacity, and the divestiture of generating companies.

Further research could apply the model to other regions and conduct similar analyses. The results could be used to evaluate different market designs. Other possible directions cover the measurement of efficiency losses of market power. However, this necessitates a model simulating strategic players' bidding behavior. It is a challenge not yet truly mastered to implement at least the most important features of electricity markets in an empirical model of strategic behavior.

4 Modeling Dynamic Constraints in Electricity Markets and the Costs of Uncertain Wind Output

4.1 Introduction

Various engineering dispatch models show the implications of intertemporal linkages for the optimal operation of a power system. In market based environments these intertemporal linkages are reflected in the prices that deviate from the variable costs of the marginal unit. The costs of starting up are usually allocated to the high demand periods and at the same time prices at the low demand periods are reduced to reflect the benefit of avoided shut-down and subsequent start-up decisions. Furthermore, power plants require a minimum output. This part-load constraint creates additional shifts between periods. Finally, higher variable costs, incurred if power stations are operated below their optimal rating, are allocated to the locally lowest demand.

For inflexible power stations like lignite, hard coal, and combined cycle gas turbines, the start of the station has to be decided several hours before delivering output. At the earlier time there is still uncertainty about the future demand, possible failures of power stations and predictions for wind-output. We represent the uncertainty using stochastic programming with recourse. In combination with the linearized unit commitment representation this is a new formulation. We then represent improved wind forecasts by aggregating different wind realizations into information sets. This allows us to quantify the value of improved wind forecasts in combination with a design that makes use of this information.

The impact of inter-temporal constraints, start-up and part load costs have been frequently discussed. Schweppe et al. (1988) developed a Lagrangian formulation to calculate the impact of inter-temporal constraints on the market equilibrium and prices. Hogan and Ring (2003) discuss how to use extra payments above marginal generation costs to pay for the additional costs. Oren and Ross describe how generators can misspecify intertemporal constraints in the balancing market, in order to exercise market power (2003). Simulations by Kreuzberg (2001), Cumperayot (2004) and also those presented in chapter 3 of this dissertation indicate that the marginal value of electricity can differ significantly from the variable costs of the marginal unit producing electricity. We analyze the optimization problem to associate an economic interpretation with the various shadow prices that arise in the formulation of the optimization problem. Bushnell (2003) discusses the impact of intertemporal constraints on price in the context of a hydro system with market power. The scarcity value (or shadow price) of water, and not the marginal costs of running the turbine in a given hour determine the dispatch and frequently set the marginal price.

The unit commitment problem exhibits non-convexities due to the indivisibilities of power plants. To illustrate the effect assume peak demand of 50.5 GW has to be covered with 1 GW units. Then 51 units have to be started up. If demand were to be increased by 0.1 GW then no additional units have to be started up and hence the marginal demand would only pay the energy costs – and not be exposed to start up costs. From this perspective the question arises how start-up costs can be earned. Hogan and Ring (2003) suggest minimum uplift payments to dispatched units in addition to energy payments to allow them at least zero profits. O'Neil et al. (2005) discuss payment approaches to compensate individual generators for additional costs. They suggest a two stage approach with an MIP model in the first stage and the integer solution to that problem fed as constraints into a linear model in the second step. The linear model allows an interpretation of shadow prices. Alternatively we can imagine uncertainty about demand or supply. Returning to the previous example, imagine that anticipated demand is uniformly distributed between 50 GW and 51 GW. Then the additional demand of 0.1 GW has to carry the start-up cost of an additional 1 GW unit with 10% probability or in expectation has to pay $1/10^{th}$ of the start up costs of a 1 GW unit. So if uncertainty about demand and supply balance exceeds the capacity of typical units at the margin then non-convexities have limited impacts on pricing decisions.

To quantify the effect of inter-temporal constraints on generation costs a dynamic linear optimization model is used to choose the power plant dispatch with minimal generation costs. The dynamic component is added through the simultaneous optimization of several consecutive load levels. The initial model is then expanded to a stochastic linear program with recourse (see Carpentier et al., 1996, Takriti et al., 2000). This enables the formalization of the uncertainty about demand, possible failure of some generation capacity or output from intermittent generation. Gröwe et al. (1995) used the same method to capture deviations of demand realization from dispatch, though ignoring unit commitment. Hobbs et al. (1999) use a unit commitment model to calculate the optimal dispatch for each of the possible realizations. Then they choose the dispatch, which performs best when tested against all of the realizations. Their approach also allows for the use of observed errors with their intertemporal structure.

We represent the uncertainty that remains several hours before dispatch; this is the time when inflexible generating units are started up. Linear programming with recourse selects a set of realizations of, and probabilities for, the parameters that are uncertain, treats this set as a deterministic set of future outcomes, and optimizes in order to minimize the expected cost function over all these realizations. The decision, according to which inflexible capacity is started up, stays fixed for all realizations of the demand and wind forecasting error, while output decisions of the started and of the flexible plants are allowed to differ between the realizations. We retain a fixed exogenously determined additional reserve quantity to compensate for power station and grid failures. This approach allows us to model the implications of uncertainty in wind predictions while retaining the linear and deterministic structure of the optimization problem.

In a third step, we model the effect of reduced uncertainty on marginal costs. In a first set of simulations, we assume a gate closure at 2:30 p.m. on the day before delivery. At the time of gate closure, planned plant dispatch must be reported to the grid operator. All deviations from nominated schedules must be served using reserve and balancing power. Some power markets allow for changes on a shorter time scale - e.g. up to one hour before dispatch in the UK - but usually liquidity in these short-term markets is too low to allow for significant adjustments. In a second set of simulations, we calculate the value of dispatching the system using the reduced forecasting error closer to dispatch. Currently, the day-ahead market determines dispatch 24 hours before demand realization, and therefore can only use rather inaccurate predictions. However, most power plants can be started on a shorter time frame, e.g. four hours, and allow the usage of better demand and wind predictions. We group the stochastic deviations into equal-sized information sets (Laffont, 1984). The improved information available closer to dispatch is represented by additional information specifying which information set will describe the possible deviations.

Based on the assumption that the impact of the individual units on dispatch costs is small in large markets we group units in different technologies. For every technology, the variable on start-ups is assumed to be continuous. So the model can for example start up any capacity between 0 and 21 GW of hard coal capacity available in the system. However, once the decision to start-up x GW has been made, production is restricted by that limit (and minimum production has to fulfill the partial load restriction). From the perspective of interpretation this follow the example of NYISO, where a unit commitment program initially calculates the optimal dispatch but prices are calculated in a second run allowing for start-up decisions of fractions of units. Alternatively Madrigal and Quintana (1998) suggest using the prices from the Lagrange relaxation, thereby smearing the start-up costs over larger ranges of the marginal demand. From the numerical perspective we can refer to the good match of modeled prices with observed prices in the German market that Kreuzberg (2001) obtained using this approach. Allowing for continuous start up decisions avoids the computational complexities that result from solving mixed integer problems (MIPs). The challenges and other solution approaches are described in Wood and Wollemberg (1996) and Sen and Kothari (1998). The models have been solved, initially with dynamic programming, genetic algorithms, Lagrangian relaxation and, recently, with branch and bound algorithms (Makkonen and Lahdelma, 2005).

Once the theoretical framework is established, we parameterize the model with realized data for the German market. We use the example of wind power generation to analyze the effects of uncertainty. We find that the costs of balancing wind power were relatively low in the German system in 2003. They could be reduced even further when a better forecast becomes available, either by implementing a later gate closure or by improvements in the wind forecasting model. We estimate that variable costs of conventional generation increase by approximately 1.4% if only 24 hour wind predictions are used to determine unit commitment. If improved wind forecasts are used and final dispatch is determined four hours before realization, then variable costs only increase by 0.6%.

The chapter is structured as follows. Subchapter 4.2 introduces the formulation of the inter-temporal constraints and analytic results on how they affect prices. Subchapter 4.3 adds uncertainty to the model using a deterministic linear equivalent of a stochastic optimization model with recourse. Subchapter 4.4 presents a model to quantify the savings brought about by reduced uncertainty. In Subchapter 4.5, this model is then parameterized with data for the German power market in the year 2003 and applied to calculate the benefits updating wind forecasts. Subchapter 4.6 concludes the chapter.

4.2 *The Economics of Intertemporal Dynamics*

We introduce three physical characteristics of power plants and the resulting intertemporal constraints. Analytic arguments are used to show how these constraints alter the marginal energy prices at different segments of the load curve.[38]

4.2.1 Modeling of Intertemporal Constraints - Thermal System

We calculate the optimal dispatch for the operation of an electricity system. To simplify the representation in this subchapter we only assume one technology and ignore uncertainty. We start with a model that only captures fuel and start-up costs. To ensure started capacity will subsequently be stopped, we include part-load constraints. In a second step, the model is expanded to also capture part-load costs.

The system operator determines the output choice X_t to maximize the system benefits $-TC$ over hours t of the day, given variable operational costs of c^x of unit and start up costs c^u, which are incurred when capacity U_t is started in period t. Maximize with respect to X, U, and D:

$$(14) \qquad -TC = -\sum_{t=1}^{T}\left(X_t c^X + U_t c^U\right).$$

The optimization is subject to the energy balance for each period (shadow price λ_t^d):

$$(15) \qquad d_t - X_t = 0 \qquad \forall t.$$

The sum of capacity started in the current and preceding periods minus the sum of stopped capacity D_t must equal or exceed current production (shadow price λ_t^{su}):

$$(16) \qquad X_t - \sum_{u=1}^{t}\left(U_u - D_u\right) \le 0 \qquad \forall t.$$

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[38] A list of symbols is shown in appendix B.

Power stations have a minimum output quantity α (with $0 \le \alpha \le 1$), below which production is not possible or only with unacceptable efficiency losses. This is represented by the part-load constraint (shadow price λ_t^{pl}):

$$(17) \qquad \alpha \cdot \sum_{u=1}^{t} \left(U_u - D_u \right) - X_t \le 0 \qquad \forall t .$$

The Lagrange function capturing these constraints is:

$$(18)\, L = -\sum_{t=1}^{T} \left(X_t c^X + U_t c^U + \lambda_t^d \left(d_t - X_t \right) + \lambda_t^{su} \left(X_t - \sum_{u=1}^{t} \left(U_u - D_u \right) \right) + \lambda_t^{pl} \left(\alpha \sum_{u=1}^{t} \left(U_u - D_u \right) - X_t \right) \right).$$

4.2.2 Modeling of Intertemporal Constraints – Hydro-Storage

The dispatch of hydro-storage capacity is another dynamic aspect optimized in our modeling approach. Hydro-storage plants are described by a capacity constraint restricting their maximal output at any time t and an energy constraint (posed by the amount of water stored in the basin). While these hydro-storage plants have variable generating costs of nearly zero, the energy constraint limits the time for which they can be dispatched.. Hence, storage water production is dispatched during hours where it can reduce total generation costs the most. This is usually during peak demand periods. Dispatch decisions for hydro-storage facilities are by their very nature intertemporal, as the production of hydro-storage in one hour takes up energy that would otherwise be available for production in other hours. Pump storage plants can increase the available energy budget by pumping during low demand periods.[39]

If hydro-storage is energy and not capacity constrained, then it flattens peaks. Therefore, the start-up costs that are usually allocated to one hour are distributed over multiple hours or peaks. Each hour then only receives a fraction of the start-up costs, and prices are less volatile.

[39] Pump-storage plants consume electricity during low price periods to pump water from a lower basin up to a higher basin. Potential energy stored in the water in the higher basin can be used for electricity production during high price periods by letting it again flow into the lower basin. With an efficiency of above 75% (consume 4 MWh during low price periods to produce 3 MWh during the peak), this is a widely used way to store electricity in regions with the right landscape.

The complete set of equations describing the optimization problem, including hydro-storage and pump-storage dispatch constraints, is described in appendix B. Equations (36), (43) and (44) contain the endogenous optimization of storage and pump-storage facilities.[40]

4.3 Modeling of Uncertainty

It is often pointed out in the literature (e.g. E.ON wind report, 2005) that the stochastic pattern of wind power generation imposes additional costs due to an increase in the required amount of balancing power and a less favorable plant dispatch. To approximate the effects of uncertainty in our linear optimization model, we introduce a set $r = 1,...,R$ of possible realizations of forecasting error[41]. As we simultaneously model 24 hours of a day[42], each of the forecasting error realizations is a vector with 24 values, one for each hour of the day. An efficient dispatch of the system must take into account the distribution of forecasting errors within each hour, and their dependence between-hours. The following example illustrates the relevance of intertemporal dependence of forecasting errors. The best response for a one-hour deviation between forecast and realized demand is to start a peaking plant with low start-up and high variable costs. In contrast, if the deviation is expected to remain over several hours, then it might be worthwhile to start a plant with higher start-up costs and lower variable costs.

We restrict ourselves to calculating dispatch situations with typical time paths of forecasting errors using observed data for these errors. The data will be described in subchapter 4.5.

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40 Optimizing 'only' 24 hours in our model, we make a simplification on inter-daily and long-run hydro dispatch decisions which we must treat as exogenous input. However, inter-seasonal hydro optimisation is not the focus of this article, as we concentrate on short-term dispatch decisions. In addition, we apply our methodology to the German market, which is somewhat influenced by hydro-storage facilities, but far less than other markets, e.g. Northern Europe.

41 We use available data for the forecasting error realizations from ISET's wind forecast for Germany in 2003.

42 To avoid the impact of boundary conditions, we always simulate three consecutive days and then report the results for the middle day.

We assume that each error realization can occur, with probability θ_r. The optimal system dispatch now involves maximizing the expected system benefit. This is represented by introducing the probability-weighted sum over all realizations. Furthermore, we introduced additional supply technologies by including the set $s = 1,...,S$ of different technologies. We avoid the problems of indivisibilities (a non-convexity) by grouping plants in similar supply technology groups[43] and assuming infinitesimal unit size in each group. Maximize with respect to $X, U,$ and D:

$$(19) \qquad -TC = -\sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{r=1}^{R}\theta_r * \left(X_{s,t,r} * \left(c_s^X - c_s^{PL}\right) + U_{s,t,r} * c_s^U + \sum_{u=1}^{t}\left(U_{s,u,r} - D_{s,u,r}\right) * c_s^{pl} \right).$$

The demand equation in (20) must be satisfied for each realization of the forecasting error $\rho_{t,r}$. In addition, we reduce demand by the average expected wind generation w_t^e.

$$(20) \qquad d_t - w_t^e + \rho_{r,t} + P_{r,t} - \sum_{s=1}^{S} X_{s,t,r} = 0$$

A power plant's generation is restricted by its installed available capacity. However, a plant must be started up to be able to produce. As was formalized in equation (17), plants can change both production as well as start-up and shut-down decisions. However, since the deviations brought about by the forecasting error's realization are, by their nature, unpredicted and arising on short notice, they must be covered by reserve and balancing capacity. This brings a crucial aspect of inflexibility into the model: some technologies do not have the flexibility to start up or shut down additional capacity on short notice. Therefore, these inflexible plants' (s^{nf}) amount of capacity started up and hence ready for operation must be identical for all possible realizations of the forecasting error. (21) shows these constraints.

$$(21) \qquad U_{s,t,r} = U_{s,t}, \quad D_{s,t,r} = D_{s,t} \qquad\qquad \forall s \,\middle|\, s \le s^{nf}, \forall t, r$$

Because of computational constraints, we can only model a limited number of system realizations. Extreme deviations, occurring with low probability, are not captured by the system realizations. We add an equation for additional reserve capacity to ensure that

[43] Our specific setup for the German market will be discussed in subchapter 4.5.

sufficient flexible and spare operating capacity is available for these cases. We also subsume other sources of uncertainty, such as unforeseen plant outages and load deviations, in this equation. We capture this by introducing a capacity constraint for reserve and balancing power:

$$(22) \qquad d_t + rc - \sum_{s=1}^{s^{nf}} \sum_{u=1}^{t} \left(UP_{s,u,r} - DN_{s,u,r} \right) - \sum_{s=s^{nf}+1}^{S} x_s^m \leq 0$$

4.4 Updating of Wind Forecasts

The uncertainty of wind power generation can be reduced by improving the quality of wind forecasts. This can either be achieved by getting a better 24-hour-ahead forecast or by using a more up-to-date forecast when deciding on plants' start-up and shut-down decisions. There is a limit to the second approach, as scheduling of inflexible plants requires sufficient lead-time. However, this lead-time of about four hours before production has not yet been achieved in most markets. In Germany, for example, plans for plant operation are decided and reported to the transmission grid operators at 2:30 p.m. the day before delivery, for all 24 hours of the delivery day. In theory, the British gate closure of one hour does undercut this lead-time; in practice, liquidity is too low in the intra-day market to allow for generators to reschedule efficiently. Postponing this notification, at least for wind power, to a later point in time would allow the use of a better wind forecast.[44]

We will measure the effect of the reduced uncertainty in the wind forecast, either by a later gate closure or by more advanced prediction models, by using a four-hour-ahead forecast instead of the 24-hour-ahead forecast. However, we cannot simply calculate a model run with the four-hour-ahead wind forecast instead of the 24 hour wind forecast, because the effect on system costs of individual wind forecast errors is in the same order of magnitude as the effect

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[44] However, lead time is not only limited by thermal plants' inflexibilities but also by the grid operators' responsibility to maintain a secure network, which necessitates early enough knowledge of expected power flows.

of improving the wind forecasts. Therefore, choosing a different set of wind forecast errors would eliminate the opportunity to compare the results of both forecast scenarios.

We therefore model this increase in information by dividing the original set for the forecasting error into different subsets. The number of possible forecasting error realizations is thus reduced in each model run. Thus, the increase in information gained by the four-hour-ahead forecast is used to decide which subset of the original set of forecasting errors is reached. This leads to a reduction in costs, as plants can operate more flexibly. Instead of one mode of operation for all possible realizations, there is now a number of different modes of operation (one for each of the newly-created subsets). An additional aspect reducing costs when moving from the 24-hour-ahead forecast to the four-hour-ahead forecast is that the remaining uncertainty in the system is also reduced. This uncertainty might be caused partly by the possibility of highly unlikely wind conditions, but also by other factors of uncertainty, such as demand forecasting errors or plant outages. We treat those aspects by introducing an additional constraint representing the reserve capacity requirement (22). The resulting effect will be analyzed separately. The results can be compared to the day-ahead forecast by running separate scenarios for each information subset and averaging over these model runs.

This clear-cut way of replacing day-ahead forecasts with four-hour forecasts gives us an upper bound to the system improvements. By the very nature of a ‘four-hour-ahead’ wind and demand forecast, only the next four hours are available. For the hours five to 24 hours ahead of dispatch, we cannot expect the same forecasting accuracy as we assume in our model.

4.5 Application to German Power Sector

We apply the model described above to the German power market. In 2003, our reference year, Germany was the country with the largest installed wind capacity: nearly 15 GW. The costs for the integration of wind power in the German system are currently the subject of lively debate (e.g. DENA, 2005), as plans for a further doubling of wind capacity until and beyond 2010 are being discussed.

Chapter 3 presented a model for the entire European dispatch, at the expense of less detailed representation of intertemporal constraints, reserves and balancing requirements. This allows for the endogenous determination of interconnector flows, which are used as exogenous input in our model due to lack of empirical data with sufficient resolution. The daily energy budgets for hydro-storage and pump-storage plants are also taken from that model. This simplification reduces price elasticity, as these parameters cannot adjust price signals in the model presented in this chapter.

In the following representation, we define model demand as German demand net of CHP, run off river hydro, expected wind generation and international power exchange. Hourly wind forecasts and realizations are provided by ISET e.V.

Generation plant data are taken from EWI's plant data base, as data on efficiencies and installed capacities are hardly published anymore.[45] We mentioned in subchapter 4.3 that we subsume supply technologies in different groups. To be more precise, we distinguish 16 supply technology groups (nuclear, three lignite, four hard coal, two combined cycle gas turbine, three open cycle gas turbine, two oil-fired technologies and one storage technology). In addition, we assume a value of lost load (VOLL) of 1500 Euro/MWh, and the price for the option to call demand-side response is set at 150 Euro/MWh. This level is assumed to make it the most expensive technology and hence a 'lender of last resort'. A VOLL of 1500 Euro/MWh is significantly lower than the 2000 Pounds/MWh in the British Pool. Nonetheless, even 1500 Euro/MWh for the provision of balancing power is likely to overestimate the costs for balancing the system, given the low probability for the last MWs of the 7000 MW reserve capacity to be called.

The perfect model of an electricity market would necessitate the simultaneous optimization of all 8760 hours of the year, but was impossible in our detailed model due to computational constraints. Therefore, we simultaneously optimize dispatch decisions for 24 hours of the day in each model run. To capture the effects of uncertainty, we allow $R=12$ forecasting error realizations per day. This gives a total of $12 \cdot 24 = 288$ marginal cost results per model run. In addition, modeling a complete daily load cycle allows us to endogenously optimize start-up and shut-down decisions, as well as the variation of storage and pump-storage capacity over these 24 hours (e.g. pumping at night and producing at maximum capacity during the hours of

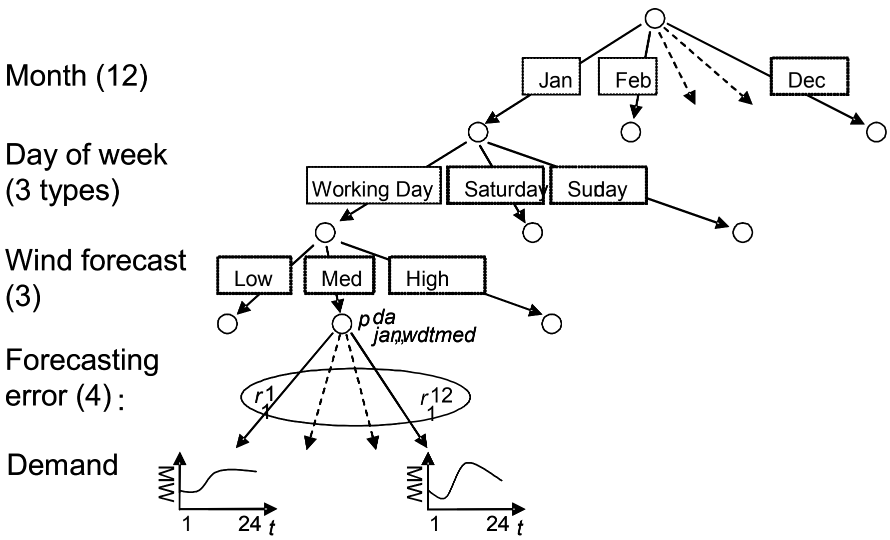
45 The last exhaustive publication, which is the foundation of the data base for Germany, was VDEW (2000).

highest demand). The resulting model has 65,000 equations and 45,000 variables and was solved on a 2 GHz desktop in about five minutes.

Nonetheless, one day is obviously not representative of a whole year. Therefore, we solve the model for twelve different months per year. In each month, three different day types are analyzed: a working day, a Saturday and a Sunday. We differentiate between three different wind-scenarios in each month by sorting them for strong, medium and low wind output. The total number of independent scenarios we compute for one year, as summarized in Figure 15, is 12x3x3=108. Multiplied by the 288 marginal cost results per scenario, we calculate 31104 different data points for the construction of a year.

Obviously, there are some dynamic effects which exceed the 24 hour period of one day. Of particular concern is hydro-storage; most storage facilities are not optimized on a daily basis, but on a weekly or even seasonal basis. While we chose not to account for these effects endogenously in our model, we consider them exogenously by choosing appropriate energy budgets for hydro-storage to different months and days of the week.

Figure 15: Total Number of Scenarios and Forecasting Error Realizations

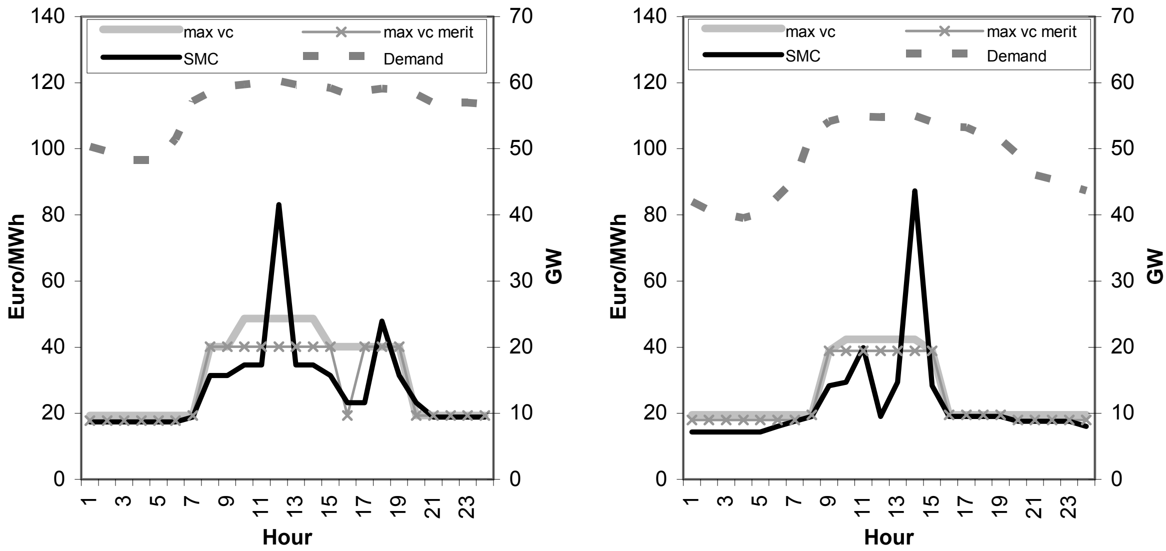


4.5.1 Intertemporal Aspects

Figure 16 shows results of the model in the absence of uncertainty about wind output. System marginal costs (SMC) represent the simulated price for each hour. The grey line 'max vc' shows the variable generating costs of the most expensive technology producing in any hour.

This line excludes the effects part-load and start-up costs have on the price. As predicted in the analytic model, the price curve is flatter with lower peak and higher off-peak prices. The analysis also illustrates the size of the errors that could result if a competitive benchmarking study were to compare observed prices with the variable costs of the most expensive unit on the system. Finally, in the curve 'max vc merit', the start-up and part load costs are not only ignored in the price formation but also for plant scheduling. With fewer constraints it is always possible to operate a unit with weakly lower variable costs. Hence, this line is bounded from above by 'max vc'.

Figure 16: Costs and Demand with Hydro Storage Dispatch, January (left) and July (right), Demand [GW] and Costs [Euro/MWh]

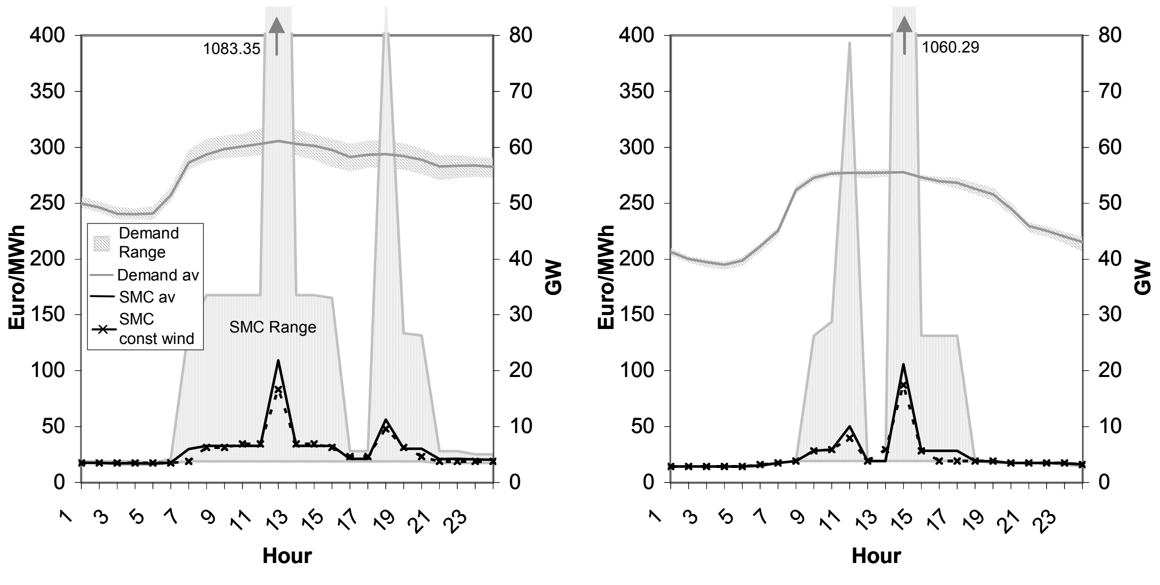


4.5.2 Uncertainty in the Wind Forecast

We use wind data for 2003, provided by ISET in Germany. The data set contains hourly wind generation and the forecasts from four hours and 24 hours before dispatch. Generation and forecasting error in the data set are normalized on the installed capacity of 14521 MW at the end of the year. We include in the analysis of each month some days of the following month, so that the total number of days is 36. They are then divided in three groups of twelve days with strong, medium and low wind generation. For each day, we calculate the difference between 24 hour forecast and wind realization. This gives us, for each of the strong, medium and low wind scenarios, 12 realizations of prediction errors, which are taken as equally probable in the subsequent simulation. We take one additional step to make our data comparable to other studies, by scaling the prediction errors with the factor 1.04, so that the standard deviation of the prediction error over the year is 7.29% of installed wind power capacity. Thus they are compatible with the DENA-Study (2005, p. 263).

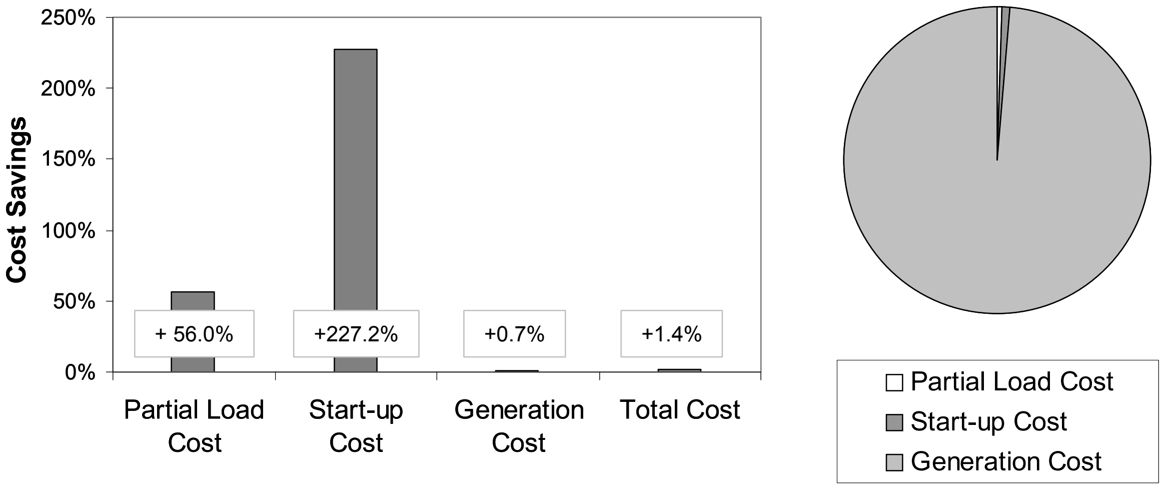
Figure 17 gives an example of the effects caused by uncertainty in the wind forecast. The demand range is determined by the maximal absolute deviations in the wind forecasting error, both upwards and downwards from the demand average. The grey-shaded SMC range is the range between minimal and maximal system marginal cost realizations. While SMC in most scenarios are grouped rather close to the average ('SMC av'), the maximum is extremely high because it bears all the costs for the provision of reserve energy from equation (22). Comparing these results with marginal costs derived without uncertainty (included in Figure 17 in the line 'SMC const wind'), we find that the wind power's uncertainty adds greatly to the volatility in SMC. However, the cost influence on the average is low.

Figure 17: Uncertainty brought about by Wind Power, Medium Wind Scenario, January (left) and July (right), Demand [GW] and Costs [Euro/MWh]



The result, that the additional costs brought about by wind power's uncertainty are low, is verified when we analyze the whole year instead of just two selected days. Figure 18 shows the changes in costs when the wind generation's volatility is added to the model. We compare two model runs with identical average wind generation. Once, the wind generation is constant over all R=12 scenarios. In the alternative, the 12 forecasting errors represent the wind power's volatility as described above. We find that both costs for part-load operation, as well as start-up costs, increase significantly as the result of the increased volatility. This was to be expected, as start-up and shut-down decisions are the key variables used to balance wind power's volatility. On the other hand, we find that the increase in generation costs is marginal. This is also plausible as average wind generation is held constant and only the volatility is changed. We find that the total cost increase as a result of wind volatility is rather low. We can understand this by looking at the right part of the graph, where we see that more than 98% of total costs are coming from generation costs, even in the model run with wind volatility. Therefore, the low increase in generation costs outweighs high relative increase in start-up and part-load costs, leading to a low overall increase in total costs.

Figure 18: Annual Cost Increase due to Volatile Wind Power Generation by Component (left) and Cost Components' Share of Total Costs (right)



4.5.3 Moving from 24-hour to Four-hour Wind Forecasts

The costs arising from volatile wind power generation can be reduced even further when a better forecast is used. In subchapter 4.4, we gave a general description of the approach taken to include the additional information becoming available when moving from a 24-hour to a four-hour forecast. However, here we describe in greater detail how we applied this to our data set. We split the 12 forecasting error realizations into three independent scenarios, with only four realizations in each scenario (see Figure 15).

The actual determination of which forecasting error belongs in which subgroup is determined by solving another optimization problem. This problem is non-linear with binary variables.

The objective function (23) shows that it sorts the twelve realizations into three groups, minimizing the total variance for all forecasting errors. The constraints ensure that

- we end up with four realizations in each subgroup (24),
- every realization is either totally in a subgroup or not at all (25),
- and every realization appears in exactly one subgroup (26).

(23)
$$\min_{V^1,V^2,V^3} \sum_{t=1}^{T}\sum_{r=1}^{R}\left(V_r^1 rr_{t,r}\right)^2 + \sum_{t=1}^{T}\sum_{r=1}^{R}\left(V_r^2 rr_{t,r}\right)^2 + \sum_{t=1}^{T}\sum_{r=1}^{R}\left(V_r^3 rr_{t,r}\right)^2 - \frac{1}{4}\left(\sum_{t=1}^{T}\left(\sum_{r=1}^{R} V_r^1 rr_{t,r}\right)^2 + \sum_{t=1}^{T}\left(\sum_{r=1}^{R} V_r^2 rr_{t,r}\right)^2 + \sum_{t=1}^{T}\left(\sum_{r=1}^{R} V_r^3 rr_{t,r}\right)^2\right)$$

s.t.

(24)
$$\sum_{r=1}^{R} V_r^1 = \sum_{r=1}^{R} V_r^2 = \sum_{r=1}^{R} V_r^3 = 4$$

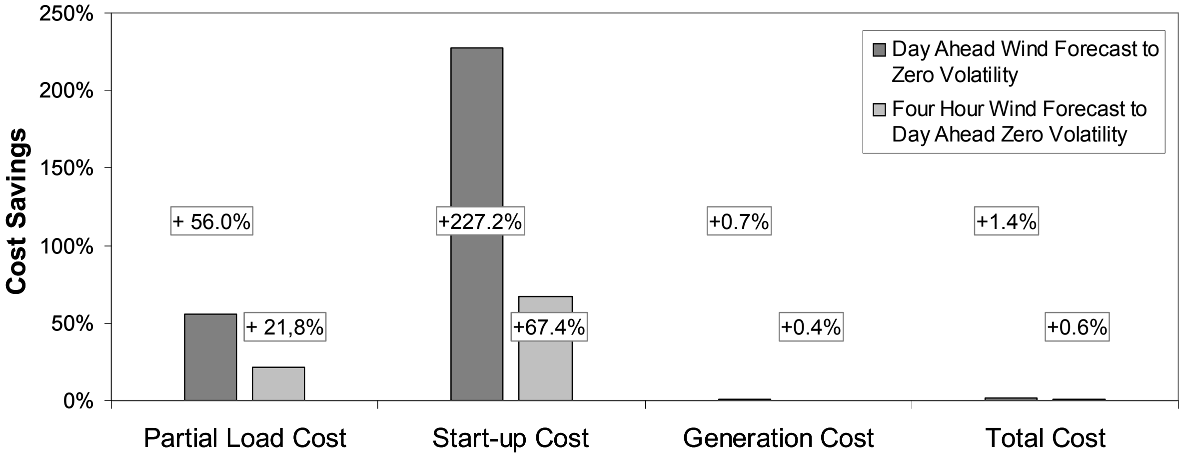
(25)
$$V_i^1 + V_i^2 + V_i^3 = 1 \qquad \forall i \in r$$

(26)
$$V_i^j \in \{0,1\} \qquad \forall i \in R, j \in \{1,2,3\}$$

Grouping the realizations lowers the standard deviation for the forecasting errors, reflecting the increase in information for the four-hour forecast. Using exactly the same realizations for the forecasting errors allows a maximum of comparison between our model runs for 24-hour and four-hour-ahead forecasts. However, we want to make sure that we achieve a most realistic improvement in the forecast's accuracy. The DENA-study (2005, p. 263) names a variance of 4.92% of installed wind power generation capacity for the four-hour-ahead forecasting error. This value is again achieved by weighting the realizations in each group accordingly.

Figure 19 shows again the increase of the different cost components when moving from the model run without wind volatility to the run with the wind volatility resulting from the day-ahead forecast. In addition, the figure now also shows the increase in total costs when the lower volatility from the four-hour-ahead forecast is used. The graph shows that all costs increase by significantly less when the improved four-hour-ahead forecast is used, instead of the day-ahead forecast. Total cost increases by only 0.6% when the improved forecast's volatility is added - instead of 1.4%, when the uncertainty from the day-ahead forecast is implemented.

Figure 19: Annual Cost Increase due to Uncertainty in Wind Generation – Day-Ahead and Four-Hour-Ahead Forecast, Relative to Zero Volatility



4.6 Conclusion

We developed a linear optimization model to analyze electricity markets. We stayed with the linear framework, as it has many advantages for the modeling of electricity markets. Firstly, linear models find unambiguous global optimums. Secondly, they are much less burdensome on computational resources. We can therefore include many aspects relevant to the modeling of electricity markets and use the extensive amount of data that is available for these markets while still keeping the model 'tractable'.[46] However, while following the established philosophy of a linear dispatch model, we extended this framework in several important directions, to model as closely as possible many features of electricity markets.

Our dynamic representation of the problem is able to represent the effects of start-up costs and part-load operation by optimizing a whole day consisting of 24 different hourly load levels simultaneously. Improving on previous models, our setup is truly sequential. The dynamic

[46] Tractable, in this context, means that we are able to run the model on a regular PC. Written in GAMS, it is able to exchange data with Excel spreadsheets. Solving one model run with the CPLEX solver takes about 10 minutes on a high-end PC. Given that one year consists of 12 months · 3 types of day per months · 3 wind scenarios in each day · 3 different groups of error realisations in the four-hour forecast, total computing time for these 324 model runs is more than one day.

modeling approach also enables us to endogenously optimize the dispatch of storage and pump-storage plants. We formalized this approach's effects on system marginal costs in subchapter 4.2.

However, we did not only implement a linear representation for the dynamic aspects of the problem, but also for uncertainty. The approach, which we chose to model uncertainty, can be referred to as stochastic programming with recourse. Some variables (in our context, start-up and shut-down decisions for inflexible plants) must be chosen before nature reveals the state of the world. However, some other variables, such as production, can be optimized after the state of the world is revealed. We illustrate this approach using wind power - a major source of uncertainty in electricity markets.

However, as the uncertainty in the wind power forecast can be reduced by either a more accurate weather forecast or a shorter time-distance between forecast and realization, we also implement the change which an increase in information would bring. We implement this using Tirole's concept of information sets, splitting the forecasting errors' possible realizations into groups and optimizing these groups separately.

In the last subchapter of this chapter, we calibrated the model developed in this article with empirical data for the German electricity market in the year 2003. We showed that following our dynamic approach, we get much more realistic marginal cost curves than with a simple static approach. System marginal costs change, especially during the very highest and lowest demand periods. However, the effects of hydro-storage capacity can counter this effect. If there is enough hydro-capacity and energy, the production profile for thermal capacity can be so flat that hardly any start-ups of thermal capacity are necessary, thus bringing down the peak and distributing start-up costs over a longer period of time.

Furthermore, we use our very detailed model to quantify the effects of wind power on reserve and balancing provision. This is one important aspect in discussions of the costs and benefits of introducing a large share of wind power into an electricity system. We showed that costs for electricity generation are increased due to wind power's volatility. However, this increase can be greatly reduced if the wind forecast can be made more accurate. The increase mostly comes from increased start-up and part-load costs. Generation costs are hardly influenced. This is in accordance with expectations, as volatility does not influence the average of the demand realizations. However, as generation costs are by far the largest cost component, the total cost increase in the electricity system from wind volatility is found to be small (1.4%). This figure is reduced to 0.6% when the four-hour-ahead forecast is used. Interpreting these figures, one has to bear in mind that we are looking at data from 2003, when Germany was well endowed with generation capacity.[47] The costs of increased wind power volatility can rise significantly when the system is closer to capacity limits. On the other hand, installed capacities can adapt in the long run to achieve an optimal integration of wind power into the system, e.g. by capacity additions in less capital-intensive flexible gas-turbines. Such long-term effects are left for further research, as we concentrated on short-term dispatch in this chapter.

In further research, the model could be extended to capture the effects of a continuous updating of the wind forecast, taking into account that additional data on the wind forecast are becoming available in every hour. This way, a decline in forecasting accuracy for those hours further ahead in the future than four hours can be modeled. In addition, the model can be extended to cover more than one model region and endogenously determine international power exchange. In addition, the model is directly applicable to many other empirical questions, such as the effect of CO_2emission costs on plant dispatch and costs or competitive benchmarking studies.

[47] The German market contained significant excess capacity before market liberalisation in 1998. While these capacities were reduced after liberalisation, this process was not finished before 2003.

5 Start-Up Costs in Electricity Markets

5.1 Introduction

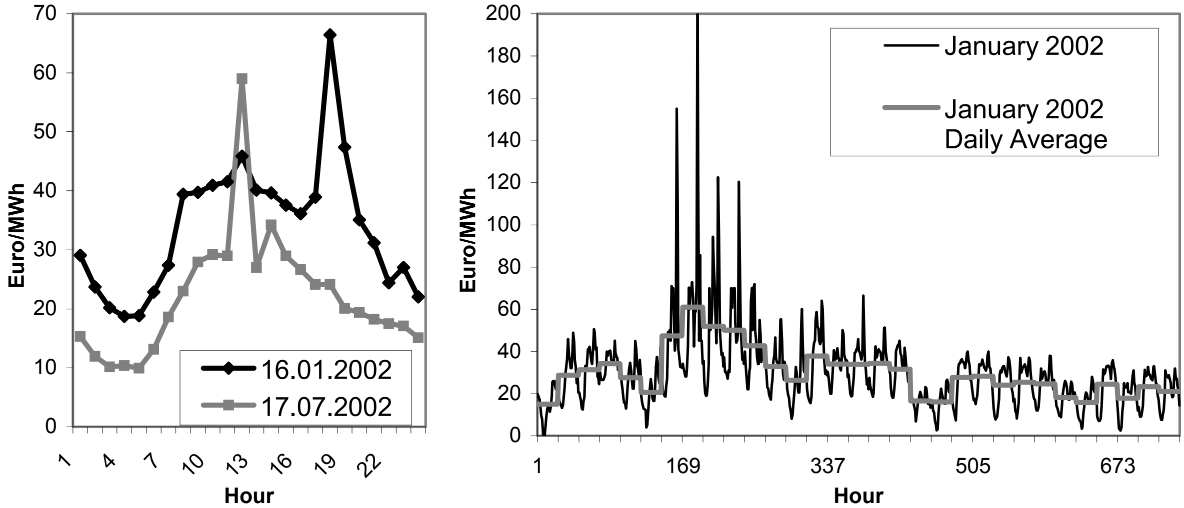
Energy markets have been liberalized in a world wide movement towards deregulation. However, this unambiguous movement came to an end as some liberalized markets, e.g. in California, turned out to be significantly flawed. Against this background the question of how much regulation is needed in energy markets is of central importance. For this assessment, the disadvantages of regulated markets have to be compared to the disadvantages of liberalized markets. The vulnerability of wholesale electricity markets to different forms of gaming turned out to be a key disadvantage in liberalized markets. Due to the good availability of data, market power in electricity markets can be measured. This is done applying competitive benchmarking approaches comparing competitive estimates of the market results either with observed market price data or with the result of strategic models. In this chapter, we will analyze the importance of start-up costs as a factor which was neglected in previous studies but is nonetheless significantly influencing the structure of a competitive price benchmark.

Numerous studies have analyzed market power in liberalized electricity generation markets (e.g. Green and Newbery 1992, Borenstein, Bushnell, and Wolak 2002). To our knowledge, all of these papers measure market power in static models neglecting dynamic intertemporal effects. Bushnell (2003) applies a dynamic model of strategic behavior in electricity generation markets focusing on the combined optimization of hydro storage and thermal units. However, even that model does not consider the effects of start-up costs. The neglect of start-up costs in many of these papers is due to the complexity start-up costs add to the problem. For example, it is hard to determine supply function equilibria even in static electricity markets and seems virtually impossible in the context of the simultaneous intertemporal analysis necessary to capture start-up costs. Nonetheless, the effects of start-up costs are recognized in these papers. Green and Newbery (1992) state that start-up costs can lead to significant price increases especially during periods of highest demand. This effect, however, is easily confused with price increases resulting from strategic behavior which is also most pronounced during high demand periods. This is problematic as the first is an efficient scarcity signal, the second the result of market power. Borenstein, Bushnell and Wolak (2002) also mention start-up costs as a neglected factor in their analysis and even raise the question in which periods start-up costs should optimally be included in power plants’ supply bids. They also recognize that start-up costs increase prices during high demand periods and decrease prices during low demand periods. The same result was discussed by Lucas and Taylor (1994) in the context of an analysis of the market design in the England and Wales electricity pool. They were even more specific stating that only start-ups at (local) maxima in demand increase start-up costs as load increases during other periods simply lead to earlier start-ups (or later shut-downs) of capacity. We show that the increase of prices during peak periods due to start-up costs and the decrease during low demand periods nearly cancel out on the average.

Start-up costs and hydro storage and pump storage dispatch are intertemporal effects influencing the structure of prices. Start-up costs are the costs associated with the start of operation for a power plant. These costs comprise the costs to heat up the boiler, costs for synchronization of the plant with the electricity grid, and also increased attrition as the result of the high changes in the temperature due to heating up a plant. Start-up costs are independent of the time of production following the start-up. Hence, the determination of the optimal dispatch is not a static problem as the optimal mode of operation in any hour depends on the hours before and after. The other dynamic component, hydro storage dispatch, is not in the focus of this chapter. See Scott and Read (1996) for a description of an optimal hydro storage dispatch and chapter 3 for a quantification of hydro storage's impact on prices.

Start-up costs emerge from the special features of electricity markets which distinguish them from many other markets. Electricity cannot be stored economically. In connection with a demand profile that exhibits strong seasonalities over the course of the day, week, and year, this leads to large fluctuations in demand. Since the different generation plants have varying productions costs, fluctuations in demand lead to fluctuations in electricity prices (Figure 20). This in turn translates directly into changing modes of operations for many plants. While it is often economical to operate a plant with high variable costs during high price (and demand) periods over the day, the same plant might shut down at night when prices are low.

Figure 20: Seasonality and Volatility in Electricity Prices, an Example from the German Power Exchange



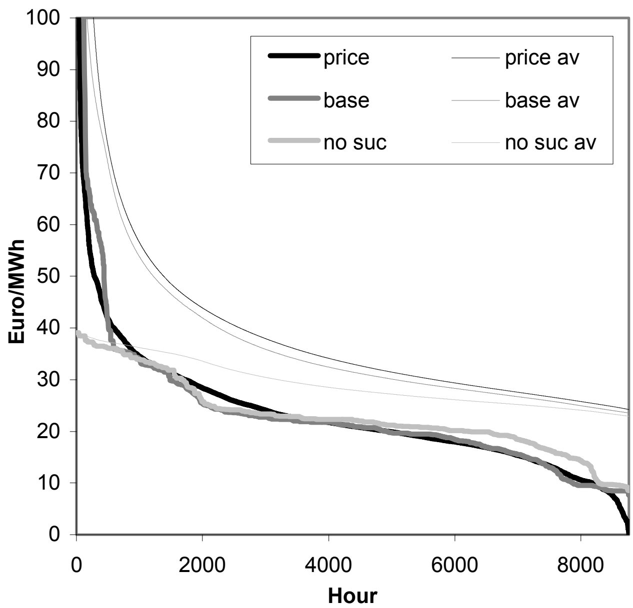
Source: Müsgens and Ockenfels (2006)

The problem of determining an efficient plant dispatch (production schedule) in the face of variable generation costs and start-up costs facing the features described above is a unit commitment problem. Such unit commitment problems are often analyzed in the context of mixed integer (MIP) models (e.g. Bard 1988). While this approach is the most exact for the problem at hand, it has some disadvantages. One is the interpretation of the dual variables in mixed integer problems. Both O'Neill et al. (2005) and Hogan and Ring (2003) describe this problem in great detail. They also present a solution which is first solving the MIP problem and then feeding the solution to the integer variables as constraints into a linear model. We chose a simpler approach by directly analyzing a linear model. This linear model neglects the effects of non-convexities caused by indivisibilities. However, it enables a more detailed analysis of other factors. We discuss in chapter 4 that this can be a reasonable simplification in large systems. Furthermore, both Figure 21 and, to much greater detail, chapter 3 show that the linear approach seems to be a reasonable simplification for the German market as model results are rather close to market data.

Hence, we know that start-up costs play a role in electricity markets. They influence both efficient dispatch and prices. Against this background, they should be entailed in electricity market models. However, the question remains how big an error is made neglecting their impact. This chapter was motivated by empirical results in our research suggesting that start-up costs are indeed an important aspect for the explanation and modeling of electricity prices.

This result is presented in Figure 21. The figure presents price duration curves for the year 2001 in the German market. Price duration curves are price curves sorted in descending order. The 'Price'-curve shows the observed market price from the German power exchange (volume weighted averages of the two power exchanges operating in the German market in 2001). The curve is based on 8760 hourly price realizations for the year. The 'price av'-curve is defined by $price\,av(h) = \frac{1}{h}\sum_{t=1}^{h} price(t)$, where h and t are the hours on the abscissa. The two other curves are derived with the linear optimization model described in chapter 4. The 'base'-curve is a model run endogenously optimizing start-up decisions and both hydro storage and thermal production taking into account uncertainty and reserve and balancing requirements. The 'no suc'-curve is the same as the base case with the exception of start-up costs which are set to zero. Both model graphs are calculated from 2592 data points. They are based on the dual variables of the demand restriction (later referred to as λ_0). These marginal costs should be the price in an efficient competitive market.

Figure 21: Start-Up Costs' Impact on the Marginal Costs an Example from the German Power Market in 2001



Source: EEX, own calculations

The graph highlights the importance of start-up costs for the structure of electricity prices. Neglecting them leads to too low prices in the high price areas in the left part of the graph and too high prices during low price periods in the right part of the graph. This obvious result is supported by the explanatory power. A regression using $base(t)$ as the only explanatory variable for $price(t)$ gives $R^2 = 0.49$. Using $nosuc(t)$, the explanatory power drops to $R^2 = 0.27$ supporting the view that start-up costs indeed are important for the price structure. While the relatively high explanatory power is in part the result of sorting the price duration curve, we showed in chapter 3 that similar models can yield good results when 24 hours for typical days per month are analyzed.

However, we also see in the figure that the annual average (the very right data points in the three '… av'-curves) is very close together for all three curves. This observation, which was also made by Kreuzberg (2001) and Cumperayot (2004), suggests that the cost increasing effect of start-up costs during high demand periods and the cost decreasing effect during low demand periods nearly cancel out.

In this chapter, we take these empirical results as motivation to perform a rigorous theoretical analysis of the effect of start-up costs in a linear optimization model. We present a simplified model capturing many effects of start-up costs. In the context of this model, we derive several theorems on the properties of the optimal solution. One key result is that the sum of marginal costs depends only on the costs of the technology with lowest total generation costs for flat generation over all periods. In fact, if demand is different over all periods, we even show that the minimum cost technology's total generation costs, defined as start-up costs of that technology plus the total number of demand periods times variable costs, equal the sum of the dual variables or shadow prices of the demand restriction which in turn equal the market price in a competitive environment. In the limit, this means that average marginal costs are equal to the variable costs of the cheapest technology – independently of start-up costs. One implication of this result is that the structure of load does not influence average marginal costs. It is important to note at this point that we are analyzing time weighted average marginal costs. Volume weighted, average marginal costs are increased as we already pointed out that start-up costs increase prices during high demand periods but lower them during low demand periods. However, the time weighted average is relevant for many aspects, e.g. investment decisions both on the supply and demand side. In addition, the base price (price for the delivery of 1 megawatt of electricity over a certain time interval, or time weighted average) is an important reference point for the market.

Furthermore, we develop an algorithm to determine the optimal solution to our problem. This algorithm determines both optimal dispatch as well as the dual variables to the primal problem without having to solve an optimization problem. As a result of this algorithm, we can show that in the absence of binding capacity limits, all technologies fulfill the zero profit condition.

We leave the analysis how these results change in the context of more detailed models for further research. However, we believe that at least partial load and hydro storage dispatch can be included in an extended version.

The chapter is structured as follows. Subchapter 5.2 presents the model used to derive our results. Subchapter 5.3 presents the results, subchapter 5.4 concludes the chapter. Appendix C in subchapter 7.3 contains both the proofs to the theorems and numerical examples to allow an easier access to the subject.

5.2 Model

We apply a linear optimization model to determine the cost minimizing power plant dispatch. The objective function is the minimization of total costs (TC) in (27):

(27) Minimize with respect to x_{ij}, x_{ij}^{+}, and x_{ij}^{-}: $TC = \sum_{j=1}^{n} \sum_{i=1}^{s} \left(x_{ij} \cdot vc_i + x_{ij}^{+} \cdot sc_i \right)$.

The model distinguishes three different groups of variables. x_{ij} is the production of technology i in period j, x_{ij}^{+} is the amount of capacity newly started and x_{ij}^{-} the amount shut down, $i, j \in \mathbb{N}$. Note that x_{ij}^{-} does not appear in the objective function as the shut down of capacity does not inflict any costs. Costs inflicted by producing a unit of x_{ij} are vc_i (variable generation costs) and by starting up one unit sc_i.

Total costs are minimized subject to the following constraints:

(28) $$d_j - \sum_{i=1}^{s} x_{ij} = 0 \qquad \forall j = 1,\ldots,n,$$

(29) $$x_{ij} - \sum_{k=1}^{j}\left(x_{ik}^{+} - x_{ik}^{-}\right) \le 0 \qquad \forall\ i = 1,\ldots,s \text{ and } j = 1,\ldots,n\ ,$$

(30) $$\alpha_i \cdot \left(\sum_{k=1}^{j}\left(x_{ik}^{+} - x_{ik}^{-}\right)\right) - x_{ij} \le 0 \qquad \forall\ i = 1,\ldots,s \text{ and } j = 1,\ldots,n\ ,$$

(31) $$\sum_{k=1}^{j}\left(x_{ik}^{+} - x_{ik}^{-}\right) - \overline{x}_i \le 0 \qquad \forall\ i = 1,\ldots,s \text{ and } j = 1,\ldots,n\ .$$

Constraint (28) states that aggregated production equals demand d in each period. (29) assures that only capacity previously started can produce and (30) is a partial load constraint guaranteeing that at least a share α_s of previously started capacity is used for production. This partial load constraint it due to technical limitations on the operation of power plants. Constraint (31) states that total capacity started up and ready to produce cannot exceed the installed available capacity $\overline{x}_i$.

However, for the analysis in this chapter, we assume that there is so much capacity that (31) is never binding. Furthermore, we set $\alpha_i = 1\ \forall i$ which means abstracting from partial load operation. In that case, inequalities (29) and (30) simplify to one equation:

(32) $$x_{ij} - \sum_{k=1}^{j}\left(x_{ik}^{+} - x_{ik}^{-}\right) = 0 \qquad \forall s,n\ .$$

We formulated that problem in standard OR notation as a maximization problem. Then, we face the following **primal** problem:

(PP) $$\begin{aligned}&\max \left\langle c,x\right\rangle\\ &s.t.\\ &\tilde{A}x = \tilde{d}\\ &x \ge 0\end{aligned}\ ,$$

where

$$x = (x_{11},\ldots,x_{1n},\ldots,x_{s1},\ldots,x_{sn},x_{11}^{+},x_{11}^{-},\ldots,x_{1n}^{+},x_{1n}^{-},\ldots,x_{s1}^{+},\ldots,x_{sn}^{-})' \in \Re^{3\cdot s\cdot n}\ ,$$

$$c = (-vc_1,\ldots,-vc_1,\ldots,-vc_s,\ldots,-vc_s,-sc_1,0,\ldots,-sc_1,0,\ldots,-sc_s,0,\ldots,-sc_s,0)' \in \Re^{3\cdot s\cdot n}\ ,$$

$\tilde{d} = (d_1,\ldots,d_n,0,\ldots,0)' \in \Re^{+(s+1)\cdot n}$, and

$$\tilde{A} = \begin{pmatrix} Id^n & Id^n & Id^n & \cdots & Id^n & 0 & 0 & & \cdots & 0 \\ Id^n & 0 & 0 & & 0 & B & 0 & 0 & \cdots & 0 \\ 0 & Id^n & 0 & & 0 & 0 & B & 0 & & 0 \\ 0 & 0 & Id^n & & 0 & 0 & 0 & B & & 0 \\ \ldots & & & & & & & & \ldots & \\ 0 & 0 & 0 & \cdots & Id^n & 0 & 0 & 0 & & B \end{pmatrix},$$

$$B = \begin{pmatrix} -1 & 1 & 0 & 0 & 0 & \cdots & 0 & 0 \\ -1 & 1 & -1 & 1 & 0 & & 0 & 0 \\ \ldots & & & & & \ldots & & \\ -1 & 1 & -1 & 1 & -1 & & -1 & 1 \end{pmatrix}.$$

Id^n is the identity matrix with dimension n.

Transforming (PP) into its **dual** program (see Schrijver (1998) for dualization procedure) and slightly rearranging gives the following program:

$$\text{(DP):}\quad \begin{aligned} &\min \langle d, \lambda_0 \rangle \\ &\lambda_0 \geq -\lambda_i - vc_i \cdot 1_n \quad \forall i = 1,\ldots,s \\ &0 \leq A\lambda_i \leq sc_i \cdot 1_n \quad \forall i = 1,\ldots,s \end{aligned}$$

with

$$A = \begin{pmatrix} 1 & 1 & \ldots & 1 \\ 0 & 1 & & \\ \ldots & & \ldots & \\ 0 & & & 1 \end{pmatrix},\ d = (d_1,\ldots,d_n)^T,\ \lambda_i = (\lambda_{i1},\ldots,\lambda_{in})^T,\quad \forall i = 0,\ldots,s \text{, and } 1_n = (\underbrace{1,\ldots,1}_{n})^T.$$

For the rearrangement we use that $B^T\lambda_i \geq (\underbrace{-sc_i, 0, \ldots, -sc_i, 0}_{2n})^T$ for $i = 1,\ldots,n$ if and only if $0 \leq A\lambda_i \leq sc_i \cdot 1_n \quad \forall i = 1,\ldots,s$.

5.3 Results

5.3.1 Time-Dependent Generation Costs and Dominated Technologies

Based on lemma 1 which we present in appendix C, we can proof the following theorem:

Theorem 1:

(DP) is equivalent to the following linear program:

$$\text{(DP*)} \quad \begin{array}{l} -\max < d, \tilde{\lambda}_0 > \\ A_j \tilde{\lambda}_0 \le \gamma_j 1_{n-j+1}, \text{for } j = 1,...,n \end{array},$$

where $\tilde{\lambda}_0 = -\lambda_0$, $A_j = \begin{pmatrix} 1 & 1 & \cdots & 1 & 1 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 1 & & 1 & 1 & 1 & 0 & & 0 & 0 \\ ... & & & & & & & & & ... \\ 0 & 0 & & 0 & 1 & 1 & 1 & & 1 & 0 \\ 0 & 0 & \cdots & 0 & 0 & 1 & 1 & \cdots & 1 & 1 \end{pmatrix}$ and

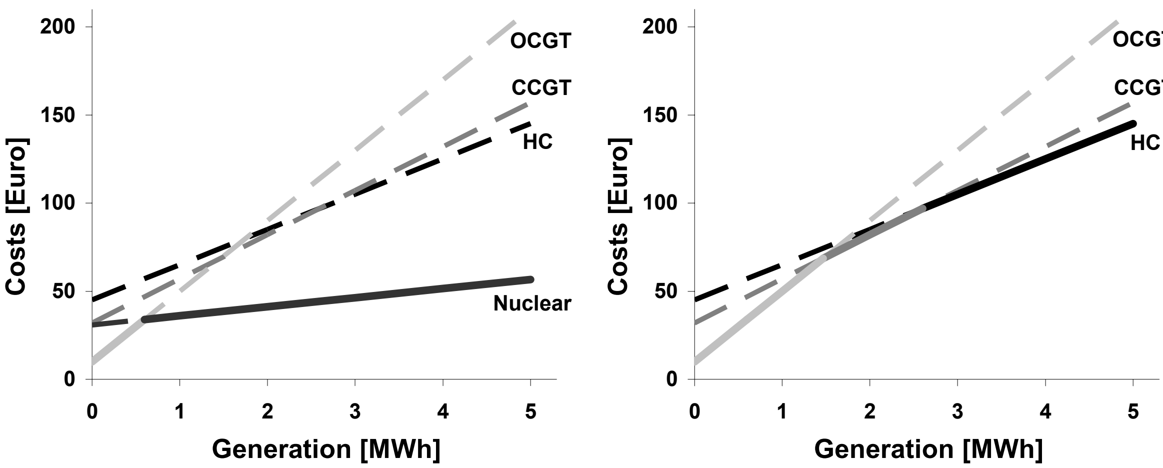
$$\gamma_j = \min_{i=1,...,s} \{ sc_i + j \cdot vc_i \}.$$

Thus, γ_j is the cost minimum over all technologies for serving a flat demand of one unit for j hours. These costs are the sum of start-up costs and *j-times* variable generation costs. The optimal solution to (DP*) is only restricted by γ_j. Hence, other things, for example the total number of different generation technologies, do not enter the problem. In addition, if a technology k is dominated by another technology i (e.g. $sc_i + j \cdot vc_i \le sc_k + j \cdot vc_k \ \forall j \le n$), the dominated technology is never used for production and can be removed from the problem without changing the optimal solution. This follows because dominated technologies do not appear in the γ_j. However, this is only true when there is sufficient capacity of the dominating technologies available.

Figure 22 shows time-dependent generation costs for four different generation technologies. The intercept in both graphs represents start-up costs, the slope represents variable costs of the different generation technologies. In both cases, the solid line represents the cost minimal generation choice for a certain length. Discretized for each full hours, this step-wise linear function determines γ_j. In the left graph, nuclear power is the cheapest generation technology even for rather short periods of production. Hard coal (HC) and combined cycle gas turbines (CCGT) are strictly dominated and would never produce. Hence, they could be taken out of the optimization problem.

However, nuclear capacity is limited. For this reason, nuclear capacity produces with maximum capacity whenever demand is higher than the installed capacity. Otherwise, all load is served by nuclear capacity. While capacity limitations are not directly implemented in our model, such a generation profile can be easily transformed into our formulation by simply reducing demand by the nuclear technology's generation. The residual demand has then to be covered by the technologies in the right part of the figure. Hence, the generation costs found in the right figure is likely to be the relevant setting for the determination of marginal costs.

Figure 22: Time-Dependent Generation Costs per MW of Capacity Started, No Binding Nuclear Capacity Limit (Left), Binding Limit (Right)



5.3.2 Algorithm to Determine the Optimal Plant Dispatch

Firstly, we define a_{ij} such that $\left(a_{1j}^T,\ldots,a_{n-1+j\,j}^T\right) := A_j \quad \forall\, j = 1,\ldots,n$ and $a_{i0} = \left(\underbrace{0,...,0}_{n}\right)^T$.

Secondly, we construct a modified primal problem (PP*) which is the dual problem of (DP*):

$$\text{(PP*)} \quad -\min \sum_{j=1}^{n} \sum_{i=1}^{n-j+1} \tilde{x}_{ij} \cdot \gamma_j$$

$$\text{s.t. } \sum_{j=1}^{n}\sum_{i=1}^{n-j+1} \tilde{x}_{ij} \cdot a_{ij} = d \text{ and } \tilde{x}_{ij} \geq 0 \text{ for } j = 1,...,n; i = 1,...,n-j+1 .$$

The $\tilde{x}_{ij}$ in (PP*) have a straight forward interpretation. $\tilde{x}_{ij}$ is the amount of capacity that starts producing in hour i and produces for the next consecutive j hours. Based on this modified primal problem, we developed the following algorithm to identify the optimal production.

Theorem 2:

Suppose $d \geq 0$. An optimal solution $\tilde{x}^* = (\tilde{x}_{1n}^*,...,\tilde{x}_{11}^*,\tilde{x}_{2\,n-1}^*,...,\tilde{x}_{n1}^*)$ to PP* can be calculated through the following iterative procedure where $i,j,k,l,s \in \mathbb{N}^+, j(i) = 1,\ldots,n-i+1$:

$$\tilde{x}_{1n}^* = \min_{k=1,...,n} d_k$$

$$\tilde{x}_{ij}^* = \min_{k=i,...,i+j-1} (d_k - \sum_{\substack{(s,l)\in \\ (\{s<i,l=1,...,n-s+1\}\cup\{s=i,l=j+1,...,n-i+1\}) \\ \cap\{s+l\geq k+1\}}} \tilde{x}_{sl}^*)$$

The algorithm determines an unambiguous solution for the dispatch problem by determining how much capacity is producing at any point in time. The algorithm's key advantage is its simplicity. In particular, it does not require any optimization software. Furthermore, the algorithm can be used to identify marginal costs λ_{0i}^*.

5.3.3 Average Electricity Price and Marginal Costs

Corollary 1:

If $d_n > 0 \;\forall n$ it follows from $\tilde{x}_{1n}^* > 0$ and the complementarity condition that

(33) $$\sum_{i=1}^{n} \tilde{\lambda}_{0i}^* = \gamma_n .$$

Furthermore, if the length n of the cycle is sufficiently large, then the start-up costs are not important at all and

(34) $$\lim_{n\to\infty}\left(\frac{1}{n}\cdot\sum_{i=1}^{n}\lambda_{0i}^*\right) = -\min_{i=1,...,s}\{vc_i\} .$$

As λ_{0i}^* is the shadow price of the demand restriction in period *i*, it is also the price estimator. Hence, (34) states that any start-up decisions during the period of observation do asymptotically not influence the average price over all periods. The average price (called 'base price' in electricity markets) is only influenced by variable costs of the generation technology with lowest marginal costs and this technology's start-up costs. In particular, the average price is neither influenced by the demand structure (very peaky or rather flat, number of peaks, …) nor by the cost parameters of any of the other technologies (e.g. peaking units). Furthermore, we have the hypothesis that (34) remains valid even if partial load operation is allowed.

In addition, the results of theorem 2 can also be used to determine the hourly marginal costs in addition to the average.

$$\sum_{i=1}^{n} \lambda_{0i} = \gamma_n$$
$$\tilde{x}_{ij}^* > 0 \Rightarrow a_{ij} \cdot \lambda_0 = \gamma_j$$
(this again follows from the complementarity condition).

When $d_i \neq d_j \; \forall i \neq j$, the solution to the problem is unambiguous. In that case, we have n independent equations determining n λ_{0i}. If we have several different equal load levels, the solution is not unambiguous but still restricted by the sum of several λ_{0i}.

5.3.4 Zero Profit Condition

Corollary 2:

In the optimum, every technology fulfills the zero profit condition.

The proof for this corollary can be found in appendix C. It is noteworthy that this corollary crucially depends on the assumption that no capacity constraint exists for the technologies.

5.4 Conclusion

Start-up cost are a cost component which should be contained in electricity price and cost estimates. However, especially models of strategic behavior have a different focus and too much complexity to endogenously model start-up costs. Hence, the question of how big an error is being made when start-up costs are neglected in an analysis is very important. While many publications qualitatively debate their impact, all but a few do not quantify them. Some empirical model results (e.g. Figure 21) are available but analytical results were lacking. This is the first chapter deriving analytical results for a linear optimization model of start-up costs in electricity markets.

We have shown that the average marginal costs in wholesale electricity markets are hardly influenced by start up costs. In a competitive market, these marginal costs, which are the dual variable of the demand restriction in the primal problem, also set the price. When the length of the observation period gets very long, the average price is purely determined by the lowest variable generation costs of all technologies. This result is independent of the height of any generation technology's start-up costs. As a result, market power estimates calculated with rather simple static models can be used without further analysis of start-up costs as long as average prices over a long period of observation are analyzed. However, the structure of prices is significantly shifted by start-up costs. Hence, as soon as only parts of a period (e.g. peak periods) are analyzed, start-up costs should play a central role in any analysis.

These results mean that the structure of demand is irrelevant for the average price. Hence, it is not true that an "unfavorable" load profile, e.g. as the result of strong seasonality in electricity generation from wind power, leads to higher average marginal costs.

Furthermore, we present a computationally simple algorithm to determine both the efficient dispatch and marginal costs in the case without partial load operation and binding capacity constraints. This algorithm was necessary to derive our results on start-up costs' impact. However, if this algorithm can be extended to cope with a more advanced set of equations incorporating some of the simplifications mentioned below, it has the potential to be used as a heuristic for dispatch decisions.

One has to bear in mind that our results are derived assuming some simplifications in the market. However, we believe that some of these simplifications could be included in our modeling approach. Firstly, we simplified the unit commitment problem from a mixed integer into a linear programming problem. We discuss in chapter 4 that this can be a reasonable simplification in large systems, especially with uncertainty and in the limit. Secondly, we abstract from partial load operation. We believe, as mentioned before, that the asymptotical behavior of the average marginal costs is still valid in the presence of partial load. A third simplification is the abstraction from binding capacity limitations. For some technologies, e.g. nuclear power, this simplification can be easily circumvented by simply subtracting available nuclear generation capacity from demand during all periods. The resulting demand can then be served by the algorithm presented. It remains the topic of further research how big the implications of this assumption are in empirical analyses. The zero profit condition does not hold anymore if capacity constraints are binding for some technologies. The constrained technologies earn positive profits.

The intertemporal constraint of hydro storage was also not implemented in the model analytically analyzed in this chapter. Furthermore, we focused on short term dispatch decisions for existing power plants in the electricity market. We did not analyze long term investment decisions. These will in particular change the result that the amount of variations in the demand curve does not change the average price as investments will also change in the long run. Last but not least, we analyzed a deterministic model.

6 Conclusion

This dissertation analyzes the economics of wholesale electricity markets. Chapter 2 discussed the development of the German wholesale market since its liberalization in 1998 and contrasted the wholesale price development with the development of the other final consumer price components (transmission, distribution, taxes, and subsidies…) to put the wholesale market into perspective. Chapters 3 and 4 presented models to capture the complex structure of the market. Both chapters contained empirical applications of these models to the German market. Chapter 3 presented the first competitive benchmarking study for Germany. The model results validated the quality of the model in a first period with only minor differences between market prices and benchmark, but also found market prices significantly above the benchmark in a second period. The difference could be attributed partly to market power. Chapter 4 focused on the increase in uncertainty brought about by an ever-increasing volatile wind generation. The costs for this uncertainty seem relatively low in the short run. Chapter 5 completed the analysis by proving that the effect of start-up costs on average prices is very small.

The results from the competitive benchmarking study in chapter 3 imply that the exercise of market power has increased over time. However, the competitive benchmarking analysis does not analyze individual companies' bidding behavior. Hence, it is not apparent which market participants are behaving strategically. It is even possible that strategic withholding in other countries is responsible for the rise of prices above the competitive benchmark in Germany. Furthermore, it remains to quantify the loss of efficiency brought about by this strategic behavior. From an economic point of view, the loss of efficiency is the crucial disadvantage of strategic behavior in electricity markets. It is caused by an undersupply of electricity due to demand reactions to higher prices. The loss is probably low, as short-term demand is rather inelastic. However, market power on electricity markets leads to additional inefficiencies: firstly, withheld capacity is replaced by capacity with higher costs, which leads to a sub-optimal dispatch; secondly, prices raised by market power during some periods can trigger sub-optimal investments. These assessments are left for further research. They necessitate an explicit modeling of strategic behavior. However, such models are static because the determination of profit-maximizing strategies and game-theoretic equilibria is already rather complex. The coupling of the two approaches seems a promising avenue for further research. In a first step, profit-maximizing strategies could be determined with a game-theoretic model.

In a second step, the dynamic models presented in this dissertation could be applied to calculate more realistic price estimates for these withholding strategies.

The results from chapter 4 imply that the German system had enough spare capacity during our period of observation to buffer the wind power's volatility at relatively low costs. We endogenously model the wind power's forecasting error, which is balanced with reserve and balancing generation. The costs for the remaining uncertainty, e.g. from unplanned plant outages, are approximated by the constant provision of additional reserve capacity. This should be integrated into future work. In addition, the calculation of necessary reserve and balancing capacity should vary over time. For example, during times of low wind forecasts less upwards reserve capacity is needed because the wind realization cannot be much lower than the forecast.

Both chapters 3 and 4 present dynamic linear optimization models. They incorporate the effects of start-up costs and hydro (pump) storage dispatch. The linearization is a simplification in some respects, however. In reality, power plants have discrete unit sizes. This implies that a mixed integer (MIP) formulation is most realistic (where units can be modeled as either being 'on' or 'off'). The disadvantage of the MIP formulation is that no start-up costs can be attributed to the dual variables of the demand restriction because a marginal load increase leads to additional units being started up with zero probability. This problem does not appear in our linear framework. Furthermore, the linear system is much easier to solve. Empirical results in this dissertation and also by Kreuzberg (2001) show that our linear model closely tracks the real market. Nonetheless, further research quantifying the differences between MIP and linear models is needed.

Chapter 5 proved our empirical observation that start-up costs are very important for the structure of prices but not for the average price. The direction for further research is rather obvious, as the proof presented in this dissertation is valid for a simplified model version. Partial load operation and hydro (pump) storage dispatch, in particular, should be included in an extended study.

7 Appendix

7.1 Appendix A (to chapter 3)

The quality of input data is absolutely crucial for the determination of marginal costs in electricity markets. The liberalization had two opposed effects on the amount of data published. Increased competition and the increased value of information have made generators much more reluctant to provide data to the public. On the other hand, regulators and grid companies are working in the opposite direction, increasing the data published in some countries. While most data are available at a monthly resolution, there is very little data available on an hourly basis. It should be mentioned that additional data simplify research, but in a strategic context they can make collusion more stable. The reason is that a player's deviations from collusive strategies are more easily detected by competitors and a threat of punishment is hence more credible.

Besides inaccurateness in the data and simplifications in the model, the most important results in this chapter, namely the strong increase in market power over time, seem robust. This is especially true since we made an effort to use a consistent data set in this analysis. The same data sources were used over the whole period of observation.[48] Nonetheless, a more detailed description of the data can make the analysis less abstract and support the understanding of the derivation of marginal cost estimators.

The presentation of all data used in the analysis would be too extensive. For that reason, monthly data for the year 2001 are described as an example. The year 2001 seems representative since it covers periods where the market seems competitive as well as other periods with large differences between prices and competitive benchmark.

Plant efficiencies and installed capacities for the different vintage classes are taken from the Institute of Energy Economics' plant database. The database comprises installed electrical and heat generating capacity, type of fuel, efficiencies and the year of construction for units in all model regions. It is updated in a tedious process collecting all available information. In

[48] The exception is some data for 2003: for example nuclear availabilities and hydro generation figures had to be taken from UCTE since some national statistics were not yet available at the time.

Germany, the database contains about 1700 units based on a publication (VDEW 2000) which covers most German plants in the year 1998. Following market liberalization, this publication is another example for the increasing value of information in the market – as it is not updated anymore because plant operators are unwilling to provide necessary data.

However, not all installed capacity is available for production and balancing services. Plants may be offline due to stochastic outages as well as scheduled maintenance. Historic realized availabilities are reported for nuclear plants.[49] However, approximated availabilities have to be used for conventional thermal capacity. These are mainly derived from older statistics (VGB 1998) covering the years until 1997 before the liberalization process increased the value of data in the market. VGB 1998 contains data both on planned as well as unplanned outages which are added to one exogenous availability parameter. As no further data is available, we assume 5% outage probability for stochastic outages in every month and for all technologies. Gas turbines are an exception as they are more reliable (2% outage probability). Planned outages are assumed to vary between 0% (January, February) and 5% (May to September). We assume the same monthly values for all years.

Start-up cost parameters for the different technologies have been collected from power plant construction companies. About half of the costs for a cold start are due to attrition. Depending on fuel prices, start-up costs for a cold start are in the order of magnitude of 10 Euro/MW for an open-cycle gas turbine and 45-50 Euro/MW for a hard coal plant. The parameter for the cool-down function varies by technology. For example, open-cycle gas turbines cool down much faster than hard coal fired plants. The parameters are also discussed in Kreuzberg (2001).

Fuel prices (Figure 23) are gathered from different sources. Hard coal prices for Northwestern Europe (free on board Amsterdam, Rotterdam, Antwerp) can be obtained from McCloskey's Coal Report. For each model region, an average markup for transshipping and transportation to plant site is added. Cross border gas prices are taken from Heren Energy's European Gas Markets. These commercial sources generally have low time lags in data publication. Fuel oil prices are provided by the Federal Statistical Office Germany.

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[49] Nuclear plant availability data for Germany can be found on www.vgb-power.de.

Figure 23: Monthly Fuel Prices at Plant, Germany 2001 [Euro/MWh ncv]

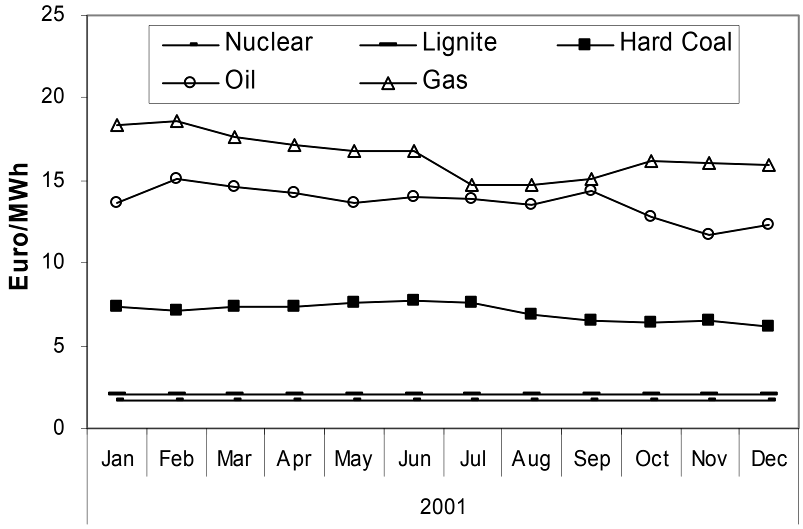
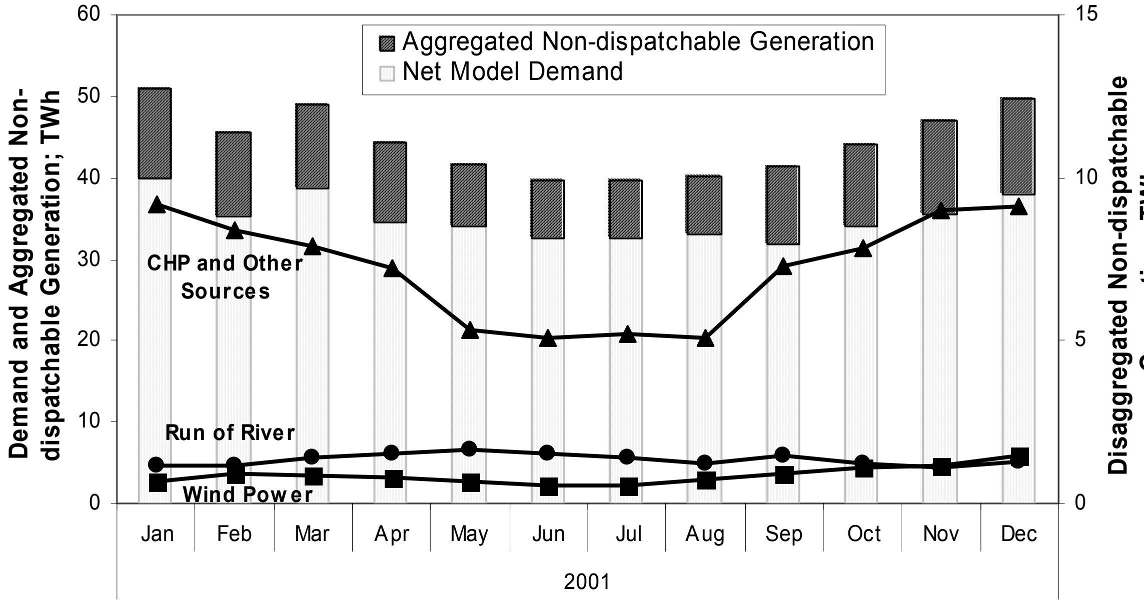


Figure 24 illustrates monthly demand data for Germany. Total demand is covered by non-dispatchable sources and "regular generation" optimized by the model. The corresponding axis for columns of model generation and aggregated non-dispatchable energy is on the left of Figure 24. Non-dispatchable energies are the aggregate of wind power generation, run of river generation, combined heat and power generation, and energy generated by other sources. Disaggregated generation by these energy sources is also shown (in lines) and corresponds to the right axis of the figure.

Figure 24: Monthly Model Demand and Generation by Non-dispatchable Energies, Germany 2001



As shown in Figure 24, total demand as well as residual model demand during the summer was much lower than during the winter months. This is caused by relatively cold and dark winters on the one hand and relatively modest summers and little air conditioning during summer on the other hand. Contra intuitively, demand in February seems to be low. However, this is simply caused by using unweighted monthly figures. Since February 2001 had 28 days, total energy consumption was naturally lower than in January and March. Demand data is derived from different publications by the Federal Statistical Office Germany[50] in connection with UCTE's hourly load profiles. Annual and monthly electricity consumption figures for other model regions are often published by national statistical offices. Additional data for many regions can be found at the regulators' home pages.

Model demand has to be corrected for the generation of non-dispatchable electricity sources. The reason is that non-dispatchable generation capacity does not react on scarcity signals. Hence, their dispatch cannot be optimized by a cost-minimizing model. Wind power is a typical example. Due to their extremely low variable costs, wind plants produce as much

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[50] One example is Statistisches Bundesamt (ed.), 2000-2003.

electricity as wind conditions allow. Wind power generation in Germany increased from 9.5 terawatt hours (TWh) in 2000 to an estimated 17.5 TWh in 2003. We see in Figure 24 that wind power generation is very volatile over the year. It is also very volatile from day to day. However, as we only analyze three characteristic days in each month, we neglect this effect by assuming an average and identical wind for all three days. However, we consider variations in the average generation over the day. In the summer months, maximal daily wind generation (during midday) can be up to 70% above minimal generation (at night). In the winter months, these hourly variations are much lower. Data on wind power generation were provided by ISET e.V.

Non-dispatchable generation also contains run of river generation. Depending on hydrological conditions, about 17 TWh of electricity are generated by run of river plants. The large monthly variations of hydro run of river generation can also be seen in Figure 24. Run of river production variations over the hours of a day are minimal. While generation profiles vary between months, we assume the same profile for working day, Saturday and Sunday.

Generation by combined heat and power plants is also deducted from gross demand to calculate model demand. However, their covering is more complicated as these plants produce both heat and electricity in a combined production process. The dispatch decision for these plants is influenced by electricity prices but other restrictions such as heat demand constitute limiting factors. For the calculation of marginal costs, we divide these plants into two groups. The dispatch of plants with a high power-to-heat ratio is assumed to be driven by electricity prices and is endogenously optimized. Plants with a low power-to-heat ratio are treated as exogenous non-dispatchable generation. Their capacity is not included in the optimization process and their production reduces model load. Additional examples of non-dispatchable production are renewable energy sources besides wind and hydro, waste combustion, and electricity produced for railways. Information on industrial CHP generation in Germany is made available by VIK. In addition, the lag of published data on CHP generation is partially solved by using another model of EWI[51].

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[51] A description of this CHP model called CEEM can be found http://www.ewi.uni-koeln.de.

In total, 115 TWh of non-dispatchable generation are deducted from German demand in the year 2000. Production for the remaining 417 TWh is endogenously optimized in the model.

Hourly model demand for the representative week is then calculated as follows: Firstly, total annual energy consumption for a region is obtained from available statistics. Secondly, monthly shares are used to break demand down to a monthly level. Thirdly, available data on the hourly structure of load are used to get hourly load curves for the representative working day, Saturday and Sunday. As described above, the same approach is taken for the non-dispatchable generation. To get the final model demand, the non-dispatchable hourly generation is subtracted from gross demand. It is important to note that demand is exogenous and price inelastic in the model. While this is an approximation (avoiding non-linearities), short-run price elasticity of demand is very small in electricity markets.

7.2 Appendix B (to chapter 4)

In the following, we give the algebra of the complete model. Following the GAMS notation, parameters (lower case letters) are exogenous and variables (capital letters) are endogenously determined as result of the optimization process.

Indices		Unit
$t = 1,...,T$	Hour	
$s = 1,...,S$	Supply technologies	
$s = 1,...,s^{nf}$	Inflexible supply technologies (unable to balance forecasting error), e.g. nuclear, lignite, hard coal, CCGT	
$s = s^{nf+1},...,S$	Flexible supply technology (can balance forecasting error), e.g. gas turbines, hydro-storage, pump-storage	
$s = S$	Last technologies in technology set is the hydro-storage and pump-storage technology	

$r = 1,\ldots,R$	Realization of forecasting error	
Parameters		
θ_r	Probability of forecasting error realization	
d_t	Expected demand	MW
rc	Reserve capacity ready to balance forecasting error	MW
w_t^e	Expected wind generation	MW
$\rho_{t,r}$	Realized forecasting error for wind generation	MW
c_s^X	Variable costs for production	Euro/MWh_{el}
c_s^U	Variable costs start-ups	Euro/MW
c_s^{PL}	Variable costs for part-load operation	Euro/MWh_{el}
x_s^m	Maximal capacity available for production	MW
p^m	Maximal capacity available for hydro pump storage plants' pumping	MW
η	Efficiency for hydro pumping plant operation	
e^m	Energy Budget with which hydro-storage and pump-storage plants enter the day	
Variables		
TC	Total Cost (objective)	Euro
$X_{s,t,r}$	Production	MW
$U_{s,t,r}$	Start-Up	MW

$D_{s,t,r}$	Shut-Down	MW
$P_{t,r}$	Pumping	MW

The objective function of global cost minimization is transformed into a maximization problem, to stick to standard OR formulation:

(35) $$\max_{X,U,D} -TC = -\sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{r=1}^{R}\theta_r * \left(X_{s,t,r} * \left(c_s^X - c_s^{PL}\right) + U_{s,t,r} * c_s^U + \sum_{u=1}^{t}\left(U_{s,u,r} - D_{s,u,r}\right) * c_s^{pl} \right)$$

s.t.

Production must cover realized demand (plus pumping):

(36) $$d_t - w_t^e + \rho_{r,t} + P_{r,t} - \sum_{s=1}^{S} X_{s,t,r} = 0 \qquad \forall r,t \qquad \lambda_t^d$$

Capacity producing must be started up:

(37) $$X_{s,t,r} - \sum_{u=1}^{t}\left(U_{s,u,r} - D_{s,u,r}\right) \le 0 \qquad \forall r,s,t \qquad \lambda_{s,t}^{su}$$

Capacity ready for operation that is unable to provide reserve (balance $rr_{r,t}$) must be constant over all realizations of $rr_{r,t}$:

(38) $$U_{s,t,r} = U_{s,t} \qquad \forall s \middle| s \le s^{nf}, \forall t,r \qquad \lambda_{s,t}^{\bar{u}}$$

(39) $$D_{s,t,r} = D_{s,t} \qquad \forall s \middle| s \le s^{nf}, \forall t,r \qquad \lambda_{s,t}^{\bar{d}}$$

Minimum part-load operation:

(40) $$\alpha_s * \sum_{u=1}^{t}\left(U_{s,u,r} - D_{s,u,r}\right) - X_{s,t,r} \le 0 \qquad \forall s,t,r \qquad \lambda_{s,t,r}^{pl}$$

Installed capacity must exceed capacity started up:

(41) $\sum_{u=1}^{t}\left(U_{s,u,r}-D_{s,u,r}\right)-x_s^m \leq 0$ $\forall s,t,r$ $\lambda_{s,t,r}^{cap}$

Capacity for positive reserve provision:

(42) $d_t - w_t^e + \rho_{r,t} + rc - \sum_{s=1}^{s^{nf}}\sum_{u=1}^{t}\left(U_{s,u,r}-D_{s,u,r}\right) - \sum_{s=s^{nf}+1}^{S} x_s^m \leq 0$ $\forall s,t,r$ $\lambda_{t,r}^{res}$

Two equations determine the dispatch of hydro-storage and pump-storage capacity. Hydro-storage and pump-storage are combined to one single technology:

(43) $P_{t,r} - p^m \leq 0$ $\forall t,r$ $\lambda_{t,r}^{pc}$

Hydro-storage and pump-storage budget:

(44) $\sum_{t=1}^{T}\left(X_{"S",t,r} - \eta P_{t,r}\right) - e^m \leq 0$ $\forall r$ $\lambda_{t,r}^{p}$

7.3 Appendix C (to chapter 5)

The following lemma is applied to transform (DP) into (DP*):

Lemma 1:

Let $y \in \Re^n$, $x \in \Re^n$,

$\Lambda = \left\{ y \,\middle|\, \exists x : y \leq x, 0 \leq A \cdot x \leq 1_n \right\}$ and $\Lambda^\pi = \left\{ y \,\middle|\, A_j \cdot y \leq 1_{n-j+1};\ j = 1,\ldots,n \right\}$

where A_j as defined above.

It is: $\Lambda = \Lambda^\pi$

Proof:

Let $y \in \Lambda$, i.e. $\exists x : \left(y \leq x \,\text{and}\, 0 \leq A \cdot x \leq 1_n \right)$.

It follows that $A_j \cdot y \le A_j \cdot x = \begin{pmatrix} \sum_{\nu=1}^{j} x_\nu \\ \dots \\ \sum_{\nu=n-j+1}^{n} x_\nu \end{pmatrix} \le 1_{n-j+1}$ because

$\sum_{\nu=\mu}^{\mu+j-1} x_\nu = \sum_{\nu=\mu}^{n} x_\nu - \sum_{\nu=\mu+j}^{n} x_\nu \le 1$ for all $\mu = 1,...,n-j+1$ (using that $\sum_{\nu=\mu}^{n} x_\nu \le 1$, $\sum_{\nu=\mu+j}^{n} x_\nu \ge 0$ for all $\mu = 1,...,n-j+1$).

Therefore, $y \in \Lambda^\pi$ and hence $\Lambda \subseteq \Lambda^\pi$.

Now, let $y \in \Lambda^\pi$. Then, it is to show that $\exists x : \left(y \le x \,\text{and}\, 0 \le A \cdot x \le 1_n \right)$. We construct x applying the following algorithm:

Step 0: Set $x = y$. If $0 \le A \cdot x$, then “end“. Otherwise, go to next step.

Step 1: Be $k^*(x)$ the largest index with property $\sum_{\nu=k^*}^{n} x_\nu < 0$.

Set $\begin{array}{ll} x'_\nu = x_\nu & \nu \ne k^* \\ x'_\nu = -\sum_{l=k^*+1}^{n} x_\nu & \nu = k^* \end{array}$

Step 2: Set $x = x'$. If $0 \le A \cdot x$ holds, then “end“. Otherwise move back to step 1.

$\tilde{x}$ has the following properties:

(a) $x' \ge x$

(b) $x' \in \Lambda^\pi$

(c) $k^*(x') < k^*(x)$ or $0 \le A \cdot x'$

The algorithm is finite because of (c). It follows from (a), (b), and (c) that the algorithm determines x with the desired properties. However, it remains to be shown that the three properties hold for x':

Ad (a): Follows from $x'_\nu = x_\nu$ for $\nu \neq k^*$ and $x'_{k^*} = x_{k^*} - \sum_{\nu=k^*}^{n} x_\nu \geq x_{k^*}$ (because $\sum_{\nu=k^*}^{n} x_\nu < 0$).

Ad (b): If no $k^*(x')$ exists, then $0 \leq A \cdot x'$. Otherwise, $k^*(x') < k^*(x)$ follows from $\sum_{\nu=k^*}^{n} x'_\nu = x'_{k^*} + \sum_{\nu=k^*+1}^{n} x'_\nu = -\sum_{\nu=k^*+1}^{n} x'_\nu + \sum_{\nu=k^*+1}^{n} x'_\nu = 0 \geq 0$.

Ad (c): We have to show that for $j = 1,...,n$ and $b = 1,...,n - j + 1$ follows: $\sum_{\nu=b}^{b+j-1} x'_\nu \leq 1$.

If $k^* < b$ or $k^* > b + j - 1$ this follows from $x'_\nu = x_\nu$ for $\nu \neq k^*$ and $x \in \Lambda^\pi$.

If $b \leq k^* \leq b + j - 1$ we have :

$$\sum_{\nu=b}^{b+j-1} x'_\nu = \sum_{\nu=b}^{k^*-1} x'_\nu + x'_{k^*} + \sum_{\nu=k^*+1}^{b+j-1} x'_\nu = \sum_{\nu=b}^{k^*-1} x_\nu - \sum_{\nu=k^*+1}^{n} x_\nu + \sum_{\nu=k^*+1}^{b+j-1} x_\nu = \sum_{\nu=b}^{k^*-1} x_\nu - \sum_{\nu=b+j}^{n} x_\nu$$

$\leq \sum_{\nu=b}^{k^*-1} x_\nu$, because $\sum_{\nu=b+j}^{n} x_\nu \geq 0$ (Note: $b + j \geq k^* + 1 > k^*$)

≤ 1, because $x \in \Lambda^\pi$.

There is $y \in \Lambda$ and hence we have shown the corollary: $\Lambda^\pi \subseteq \Lambda$. □

Proof of Theorem 1:

(DP) can be written as follows:

$$\min < d, \lambda_0 >$$

$$\frac{-\lambda_0 - vc_i \cdot 1_n}{sc_i} \leq \frac{\lambda_i}{sc_i} \text{ and } 0 \leq A \cdot \frac{\lambda_i}{sc_i} \leq 1_n \text{ for } i = 1,...,s.$$

Applying corollary 1 with $y = \dfrac{-\lambda_0 - vc_i \cdot 1_n}{sc_i}$ and $x = \dfrac{\lambda_i}{sc_i}$ leads to the following equivalent representation:

$$\min < d, \lambda_0 >$$

$$A_j \cdot \frac{-\lambda_0 - vc_i \cdot 1_n}{sc_i} \leq 1_{n-j+1},\ j = 1,\dots,n,\ i = 1,\dots,s$$

Slightly rephrasing that expression and applying that $A_j \cdot 1_n = j \cdot 1_{n-j+1}$ lead to:

$$\min < d, \lambda_0 >$$

$$A_j \cdot (-\lambda_0) \leq (sc_i + j \cdot vc_i) \cdot 1_{n-j+1},\ j = 1,\dots,n,\ i = 1,\dots,s$$

Theorem 1 follows from the definition of γ_j and transforming $\tilde{\lambda}_0 = -\lambda_0$. □

Proof of Theorem 2:

We stated in theorem 2 that an optimal solution x^* to PP* can be calculated with the following algorithm:

$$\tilde{x}^*_{1n} = \min_{k=1,\dots,n} d_k$$

$\tilde{x}^*_{ij} = \min_{k=i,\dots,i+j-1} (d_k - \sum \tilde{x}^*_{sl})$ where the sum is over $(s,l) \in \left(\{s < i, l = 1,\dots,n-s+1\} \cup \{s = i, l = j+1,\dots,n-i+1\}\right) \cap \{s + l \geq k+1\}$.

Proof:

Suppose $\tilde{x}'^{1n} = (\tilde{x}'^{1n}_{1n},\dots,\tilde{x}'^{1n}_{11},\tilde{x}'^{1n}_{2\,n-1},\dots,\tilde{x}'^{1n}_{n1})$ is optimal with $\tilde{x}'^{1n}_{1n} < \min_{k=1,\dots,n} d_k$. Note, that $\tilde{x}'^{1n}_{1n} > \min_{k=1,\dots,n} d_k$ is impossible without the permissibility of partial load. It that case, we must have

$$\sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq n}}^{n-i+1} \tilde{x}'^{1n}_{ij} \cdot a_{ij} = d - \tilde{x}'^{1n}_{1n} \cdot a_{1n} > 0\,. \tag{45}$$

As an implication of (45), we can construct indices meeting the following properties:

1. $\tilde{x}'^{1n}_{i_l j_l} > 0, l = 1,...,L$ This first property obviously ensures that all $\tilde{x}'^{1n}_{i_l j_l}$ are strictly positive.
2. $i_1 = 1, i_L + j_L - 1 = n$ This property ensures that the production schedule starts at the beginning and ends in the last period.
3. $i_l < i_{l+1}, l = 1,..., L-1$ The third property means that the schedule moves strictly to the right, each starting point is later than the one before.
4. $i_l + j_l < i_{l+2}$ This means that there must be a positive distance between the end of slice l and the beginning of slice $l+2$.
5. $i_l + j_l - 1 < i_{l+1} + j_{l+1} - 1, l = 1,..., L-1$ This property states that the end points also move to the right.

These indices are constructed as follows: firstly, define $j(i) = \max\limits_{\substack{k=1,...,n \\ \tilde{x}^{1n}_{ik} > 0}} k$. Secondly, the first index is given by $i_1 = 1, j_1 = j(i_1)$. Following indices are determined by the minimum: $i_{l+1} = \min\limits_{i \in \{s \in \mathbb{N} | i_l < (s | s + j(s) > i_l + j_l - 1)\}} i$, $j_{l+1} = j(i_l)$. Finally, the procedure finishes with indices i_L and $j_L = j(i_L)$ if $i_L + j_L - 1 = n$.

Once these indices fulfilling (1) to (5) are constructed, it follows as an implication that $\sum\limits_{l=1}^{L} a_{i_l j_l} = a_{1n} + \sum\limits_{l=1}^{L-1} a_{i_{l+1}\ i_l + j_l - i_{l+1}}$.

$\gamma(t) = \min\limits_{i=1,\dots,s} \{sc_i + t \cdot vc_i\} \forall t = 0, \dots, n$ is both monotone and concave with respect to t. Using standard properties of such a function (Avriel 1976) we can show that: $\sum\limits_{l=1}^{L} \gamma_{j_l} \leq \gamma_n + \sum\limits_{l=1}^{L-1} \gamma_{i_l + j_l - i_{l+1}}$.

Hence, we can determine a new valid optimal solution:

$$\tilde{x}'^{1n1}_{i_l j_l} = \tilde{x}'^{1n}_{i_l j_l} - \min_{l=1,...,L} \tilde{x}'^{1n}_{i_l j_l}, l = 1,..., L$$

$$\tilde{x}'^{1n}_{i_{l+1}\ i_l + j_l - i_{l+1}}{}^{1} = \tilde{x}'^{1n}_{i_{l+1}\ i_l + j_l - i_{l+1}} + \min_{l=1,...,L} \tilde{x}'^{1n}_{i_l j_l}, l = 1,..., L-1$$

$$\tilde{x}'^{1n1}_{1n} = \tilde{x}'^{1n}_{1n} + \min_{l=1,\dots,L} \tilde{x}'^{1n}_{i_l j_l}, l = 1,\dots,L$$

This procedure can be repeated until $\tilde{x}'^{1nm_{1n}}_{i_l j_l} = \min_{k=1,\dots,n} d_k$ for an m_{1n}. The procedure is finite because (i_{l^*}, j_{l^*}) with $\tilde{x}'^{1n}_{i_{l^*} j_{l^*}} = \min_{l=1,\dots,L} \tilde{x}'^{1n}_{i_l j_l}$ is not needed and remains zero in all following iteration steps. Because the number of possible index combinations is finite, the procedure ends after a finite number of steps.

The reasoning for the following values is analogous, based on the fact that all components of vector $d - \sum_{(s,l)\ iterated} \tilde{x}^*_{sl}$ are strictly greater zero. □

As a remark, it is impossible that an optimal solution found in a single step has components exceeding zero. As we postulate, they will be equal to zero. This follows from the structure of the restrictions which necessarily force them to be zero (see first case).

This iterative procedure unambiguously determines all components of $\tilde{x}^* = (\tilde{x}^*_{1n},\dots,\tilde{x}^*_{11},\tilde{x}^*_{2\,n-1},\dots,\tilde{x}^*_{n1})$. Hence, it must be a solution to the problem.

Lemma 2 (Solution to the Algorithm Is Unambiguous)

If $d_i \neq d_j$ for all $i \neq j$, then the optimal solution determined with the algorithm described is unambiguous. Note that $d_i \neq d_j$ is a very weak assumption in reality as it is very reasonable to assume that $d_i \in \mathbb{R}^+$.

The proof for this lemma follows directly from the proof of theorem 2. Because the solution to the algorithm is strictly larger than zero, exactly n of the $\tilde{x}^*_{ij}$ are larger than zero and the solution is a non-degenerate corner. Hence, the dual solution is unambiguous.

Proof of Corollary 2

The zero profit condition is fulfilled for the whole market as a direct result of the duality theorem applied to (DP*) and (PP*) and related complementarity conditions:

$$\begin{aligned}\left\langle \tilde{x}^*, \gamma \right\rangle &= \left\langle \tilde{x}^*, \hat{A}^T \lambda_0^* \right\rangle \\ &= \left\langle \hat{A}\tilde{x}^*, \lambda_0^* \right\rangle \quad \text{with } \hat{A} = \left(\underbrace{a_{1\,n}, \ldots, a_{1\,1}, a_{2\,n-1}, \ldots, a_{2\,1}, \ldots, a_{1\,1}}_{\frac{n(n+1)}{2}} \right) \\ &= \left\langle d, \lambda_0^* \right\rangle\end{aligned}$$

When we apply the mapping $\pi^s(\tilde{x}) = \left(\pi^s_{1n}(\tilde{x}), \ldots, \pi^s_{n1}(\tilde{x})\right)$ (where $\pi^s_{ij}(\tilde{x}) = \begin{cases} \tilde{x}_{ij}, & \gamma_j = sc_s + j \cdot vc_s \\ 0, & otherwise \end{cases}$) to the above relations, we can derive the zero profit conditions for every technology (again using the complementarity conditions):

$\left\langle \pi^s\left(\tilde{x}^*\right), \gamma \right\rangle = \left\langle \pi^s\left(\tilde{x}^*\right), \hat{A}^T \lambda_0^* \right\rangle = \left\langle \hat{A}\pi^s\left(\tilde{x}^*\right), \lambda_0^* \right\rangle = \left\langle d^s, \lambda_0^* \right\rangle$ where d^s is the share of demand supplied by technology s. □

An Example for the Algorithm Determining the Optimal $\tilde{x}^*_{ij}$:

In the following, we will illustrate the algorithm determining the optimal $\tilde{x}^*_{ij}$. We do this for an example where we assume n=6 and $d_k = (3,1,9,7,5,4)$. We assume $d_i \neq d_j$ so we receive an unambiguous solution (Lemma 2).

We start the algorithm by setting

$$\tilde{x}^*_{15} = \min_{k=1,\ldots,5} d_k = 1$$

The other $\tilde{x}^*_{ij}$ of the optimal solution $\tilde{x}^* = (\tilde{x}^*_{1n}, \ldots, \tilde{x}^*_{11}, \tilde{x}^*_{2\,n-1}, \ldots, \tilde{x}^*_{n1})$ should optimally be determined backwards starting with $\tilde{x}^*_{1\,n-1}$.

$$\begin{aligned}\tilde{x}^*_{14} &= \min_{k=1,2,3,4} (d_k - \sum_{\substack{(s,l)\in \\ (\{\ \}\cup\{s=1,l=5\}) \\ \cap\{s+l\geq k+1\}}} \tilde{x}^*_{sl}) \\ &= \min\left\{d_1 - \left(\tilde{x}^*_{15}\right), d_2 - \left(\tilde{x}^*_{15}\right), d_3 - \left(\tilde{x}^*_{15}\right), d_4 - \left(\tilde{x}^*_{15}\right)\right\} \\ &= \min\left\{d_1 - 1, d_2 - 1, d_3 - 1, d_4 - 1\right\} \\ &= \min\left\{2,0,8,6\right\} \\ &= 0\end{aligned}$$

$$\begin{aligned}
\tilde{x}_{13}^{*} &= \min_{k=1,2,3}(d_k - \sum_{\substack{(s,l)\in \\ (\{\ \}\cup\{s=1,l=4,\ldots,5\}) \\ \cap\{s+l\geq k+1\}}} \tilde{x}_{sl}^{*}) \\
&= \min\left\{d_1 - \left(\tilde{x}_{14}^{*} + \tilde{x}_{15}^{*}\right), d_2 - \left(\tilde{x}_{14}^{*} + \tilde{x}_{15}^{*}\right), d_3 - \left(\tilde{x}_{14}^{*} + \tilde{x}_{15}^{*}\right)\right\} \\
&= \min\left\{d_1 - \left(0+1\right), d_2 - \left(0+1\right), d_3 - \left(0+1\right)\right\} \\
&= \min\left\{2,0,8\right\} \\
&= 0
\end{aligned}$$

$$\begin{aligned}
\tilde{x}_{12}^{*} &= \min_{k=1,2}(d_k - \sum_{\substack{(s,l)\in \\ (\{\ \}\cup\{s=1,l=3,\ldots,5\}) \\ \cap\{s+l\geq k+1\}}} \tilde{x}_{sl}^{*}) \\
&= \min\left\{d_1 - \left(\tilde{x}_{13}^{*} + \tilde{x}_{14}^{*} + \tilde{x}_{15}^{*}\right), d_2 - \left(\tilde{x}_{13}^{*} + \tilde{x}_{14}^{*} + \tilde{x}_{15}^{*}\right)\right\} \\
&= \min\left\{d_1 - \left(0+0+1\right), d_2 - \left(0+0+1\right)\right\} \\
&= \min\left\{2,0\right\} \\
&= 0
\end{aligned}$$

$$\begin{aligned}
\tilde{x}_{11}^{*} &= \min_{k=1}(d_k - \sum_{\substack{(s,l)\in \\ (\{\ \}\cup\{s=1,l=2,\ldots,5\}) \\ \cap\{s+l\geq k+1\}}} \tilde{x}_{sl}^{*}) \\
&= \min\left\{d_1 - \left(\tilde{x}_{12}^{*} + \tilde{x}_{13}^{*} + \tilde{x}_{14}^{*} + \tilde{x}_{15}^{*}\right)\right\} \\
&= d_1 - \left(0+0+0+1\right) \\
&= 2
\end{aligned}$$

$$\begin{aligned}
\tilde{x}_{24}^{*} &= \min_{k=2,\ldots,5}(d_k - \sum_{\substack{(s,l)\in \\ (\{(1,1),\ldots,(1,5),\}\cup\{s=2,l=\varnothing\}) \\ \cap\{s+l\geq k+1\}}} \tilde{x}_{sl}^{*}) \\
&= \min\begin{pmatrix} d_2 - \left(\tilde{x}_{12}^{*} + \tilde{x}_{13}^{*} + \tilde{x}_{14}^{*} + \tilde{x}_{15}^{*}\right), d_3 - \left(\tilde{x}_{13}^{*} + \tilde{x}_{14}^{*} + \tilde{x}_{15}^{*}\right), \\ d_4 - \left(\tilde{x}_{14}^{*} + \tilde{x}_{15}^{*}\right), d_5 - \left(\tilde{x}_{15}^{*}\right) \end{pmatrix} \\
&= \min\left(0,8,6,3\right) \\
&= 0
\end{aligned}$$

$$\tilde{x}_{23}^* = \min_{k=2,\dots,4}(d_k - \sum_{\substack{(s,l)\in \\ (\{(1,1),\dots,(1,5),\}\cup\{(2,4)\}) \\ \cap\{s+l\geq k+1\}}} \tilde{x}_{sl}^*)$$

$$= \min\begin{pmatrix} d_2 - \left(\tilde{x}_{12}^* + \tilde{x}_{13}^* + \tilde{x}_{14}^* + \tilde{x}_{15}^* + \tilde{x}_{24}^*\right), d_3 - \left(\tilde{x}_{13}^* + \tilde{x}_{14}^* + \tilde{x}_{15}^* + \tilde{x}_{24}^*\right), \\ d_4 - \left(\tilde{x}_{14}^* + \tilde{x}_{15}^* + \tilde{x}_{24}^*\right) \end{pmatrix}$$

$$= \min\left(0,8,6\right)$$

$$= 0$$

$$\tilde{x}_{22}^* = \min_{k=2,\dots,3}(d_k - \sum_{\substack{(s,l)\in \\ (\{(1,1),\dots,(1,5),\}\cup\{(2,3),(2,4)\}) \\ \cap\{s+l\geq k+1\}}} \tilde{x}_{sl}^*)$$

$$= \min\left(d_2 - \left(\tilde{x}_{12}^* + \tilde{x}_{13}^* + \tilde{x}_{14}^* + \tilde{x}_{15}^* + \tilde{x}_{23}^* + \tilde{x}_{24}^*\right), d_3 - \left(\tilde{x}_{13}^* + \tilde{x}_{14}^* + \tilde{x}_{15}^* + \tilde{x}_{23}^* + \tilde{x}_{24}^*\right)\right)$$

$$= \min\left(0,8\right)$$

$$= 0$$

$$\tilde{x}_{21}^* = \min_{k=2}(d_k - \sum_{\substack{(s,l)\in \\ (\{(1,1),\dots,(1,6),\}\cup\{(2,3),(2,4),(2,5)\}) \\ \cap\{s+l\geq k+1\}}} \tilde{x}_{sl}^*)$$

$$= \min\left(d_2 - \left(\tilde{x}_{12}^* + \tilde{x}_{13}^* + \tilde{x}_{14}^* + \tilde{x}_{15}^* + \tilde{x}_{22}^* + \tilde{x}_{23}^* + \tilde{x}_{24}^*\right)\right)$$

$$= 0$$

$$\tilde{x}_{33}^* = \min_{k=3,\dots,5}(d_k - \sum_{\substack{(s,l)\in \\ (\{(1,1),\dots,(1,5),(2,1),\dots,(2,4)\}\cup\{s=3,l=\varnothing\}) \\ \cap\{s+l\geq k+1\}}} \tilde{x}_{sl}^*)$$

$$= \min\begin{pmatrix} d_3 - \left(\tilde{x}_{13}^* + \tilde{x}_{14}^* + \tilde{x}_{15}^* + \tilde{x}_{22}^* + \tilde{x}_{23}^* + \tilde{x}_{24}^*\right), \\ d_4 - \left(\tilde{x}_{14}^* + \tilde{x}_{15}^* + \tilde{x}_{23}^* + \tilde{x}_{24}^*\right), d_5 - \left(\tilde{x}_{15}^* + \tilde{x}_{24}^*\right) \end{pmatrix}$$

$$= \min\left(8,6,3\right)$$

$$= 3$$

$$\tilde{x}_{32}^* = \min_{k=3,\dots,4}(d_k - \sum_{\substack{(s,l)\in \\ (\{(1,1),\dots,(1,5),(2,1),\dots,(2,4)\}\cup\{s=3,l=3\}) \\ \cap\{s+l\geq k+1\}}} \tilde{x}_{sl}^*)$$

$$= \min\begin{pmatrix} d_3 - \left(\tilde{x}_{13}^* + \tilde{x}_{14}^* + \tilde{x}_{15}^* + \tilde{x}_{22}^* + \tilde{x}_{23}^* + \tilde{x}_{24}^* + \tilde{x}_{33}^*\right), \\ d_4 - \left(\tilde{x}_{14}^* + \tilde{x}_{15}^* + \tilde{x}_{23}^* + \tilde{x}_{24}^* + \tilde{x}_{33}^*\right) \end{pmatrix}$$

$$= \min\left(5,3\right)$$

$$= 3$$

$$\tilde{x}^*_{31} = \min_{k=3}(d_k - \sum_{\substack{(s,l)\in \\ (\{(1,1),\ldots,(1,5),(2,1),\ldots,(2,4)\}\cup\{(3,2),(3,3)\}) \\ \cap\{s+l\geq k+1\}}} \tilde{x}^*_{sl})$$
$$= \min\left(d_3 - \left(\tilde{x}^*_{13} + \tilde{x}^*_{14} + \tilde{x}^*_{15} + \tilde{x}^*_{22} + \tilde{x}^*_{23} + \tilde{x}^*_{24} + \tilde{x}^*_{32} + \tilde{x}^*_{33}\right)\right)$$
$$= 9 - \left(0+0+1+0+0+0+3+3\right)$$
$$= 2$$

$\vdots$

$$\tilde{x}^*_{51} = \min_{k=5}(d_k - \sum_{\substack{(s,l)\in \\ (\{(1,1),\ldots,(1,5),(2,1),\ldots,(2,4),\ldots,(4,1),(4,2)\}\cup\{\varnothing\}) \\ \cap\{s+l\geq k+1\}}} \tilde{x}^*_{sl})$$
$$= \min\left(d_5 - \left(\tilde{x}^*_{15} + \tilde{x}^*_{24} + \tilde{x}^*_{33} + \tilde{x}^*_{42}\right)\right)$$
$$= \min\left(4 - \left(1+0+3+0\right)\right)$$
$$= 0$$

Once the $\tilde{x}^*_{ij}$ are determined, we can set up the set of equations defining λ_{0i}. We know that all those $\tilde{x}^*_{ij} > 0$ give us a binding equation. Hence,

$$\tilde{x}^*_{15} = 1 \Rightarrow \lambda_{01} + \lambda_{02} + \lambda_{03} + \lambda_{04} + \lambda_{05} = \gamma_5$$
$$\tilde{x}^*_{11} = 2 \Rightarrow \lambda_{01} = \gamma_1$$
$$\tilde{x}^*_{33} = 3 \Rightarrow \lambda_{03} + \lambda_{04} + \lambda_{05} = \gamma_3$$
$$\tilde{x}^*_{32} = 1 \Rightarrow \lambda_{03} + \lambda_{04} = \gamma_2$$
$$\tilde{x}^*_{31} = 1 \Rightarrow \lambda_{03} = \gamma_1$$

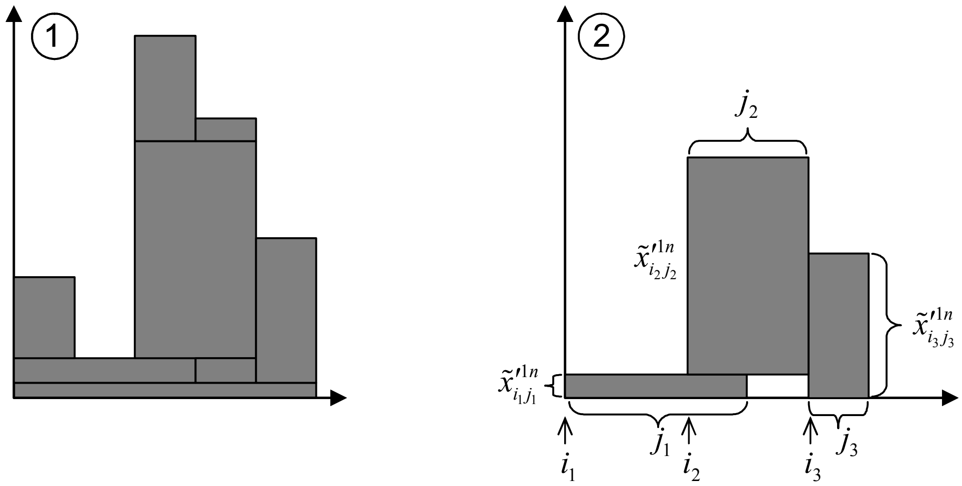
In a first step, we can use $\tilde{x}^*_{31} = 1 \Rightarrow \lambda_{03} = \gamma_1$ to determine $\lambda_{04} = \gamma_2 - \lambda_{03} = \gamma_2 - \gamma_1$. From there, it follows in a next step that $\tilde{x}^*_{33} = 3 \Rightarrow \lambda_{05} = \gamma_3 - \lambda_{03} - \lambda_{04} = \gamma_3 - \gamma_2$. The last component of the price vector is then $\lambda_{02} = \gamma_5 - \lambda_{01} - \lambda_{03} - \lambda_{04} - \lambda_{05} = \gamma_5 - \gamma_1 - \gamma_3$.

An Example Illustrating the Proof of the Algorithm in Theorem 2

Figure 25 shows indices meeting the criteria 1. to 5. specified in the proof to the theorem. In the left figure (1), we have an exemplary problem with $n = 5$ periods and demand $d = (3,1,9,7,4)^T$. Furthermore, (1) has an exemplary production schedule which is sub-optimal as $\tilde{x}'^{1n}_{1n} < \min_{k=1,\ldots,n} d_k$. We start the production schedule for all capacity started in period 1

($\tilde{x}'^{1n}_{1j}$) in dark grey and move step by step to a very light grey for all capacity started in the last period ($\tilde{x}'^{1n}_{51}$).

Figure 25: Indices Meeting Criteria 1. to 5.



Out of this schedule, we select three $\tilde{x}'^{1n}_{i_l j_l}$ satisfying 1. to 5. These are $\tilde{x}'^{1n}_{13} = \tilde{x}'^{1n}_{i_1 j_1}$, $\tilde{x}'^{1n}_{32} = \tilde{x}'^{1n}_{i_2 j_2}$, $\tilde{x}'^{1n}_{51} = \tilde{x}'^{1n}_{i_3 j_3}$. In (2), these are moved vertically on the X-axis and relabeled $\tilde{x}'^{1n}_{i_l j_l}$ with $l = 1,\ldots,3$. Do these selected $\tilde{x}'^{1n}_{i_l j_l}$ satisfy the proposed conditions 1. to 5.? They satisfy the first property as $\tilde{x}'^{1n}_{i_l j_l} > 0$ for all $l = 1,\ldots,3$. They also satisfy 2. as the first selected x starts in period one $i_1 = 1$ and the schedule ends in n (the last x is $\tilde{x}'^{1n}_{51}$, where $i_L + j_L - 1 = 5 + 1 - 1 = 5 = n$). The third property $i_l < i_{l+1}, l = 1,..., L-1$ is also satisfied as $i_1 = 1 < i_2 = 3 < i_3 = 5$. In can be seen in the figure that the fourth property is also satisfied. It is also clear from the analytics as $i_1 + j_1 = 4 < i_3 = 5$. The fifth property is satisfied: $i_1 + j_1 - 1 = 3 < i_2 + j_2 - 1 = 4 < i_3 + j_3 - 1 = 5$.

As a result: $\sum_{l=1}^{L} a_{i_l j_l} = a_{1n} + \sum_{l=1}^{L-1} a_{i_{l+1}\, i_l + j_l - i_{l+1}}$

$$\sum_{l=1}^{L} a_{i_l j_l} = a_{13} + a_{32} + a_{51} = \begin{pmatrix}1\\1\\1\\0\\0\end{pmatrix} + \begin{pmatrix}0\\0\\1\\1\\0\end{pmatrix} + \begin{pmatrix}0\\0\\0\\0\\1\end{pmatrix} = \begin{pmatrix}1\\1\\2\\1\\1\end{pmatrix}$$

$$= a_{1n} + \sum_{l=1}^{L-1} a_{i_{l+1}\ i_l + j_l - i_{l+1}} = a_{15} + a_{i_2\ i_1 + j_1 - i_2} + a_{i_3\ i_2 + j_2 - i_3} = a_{16} + a_{31} + a_{50}$$

$$= \begin{pmatrix}1\\1\\1\\1\\1\end{pmatrix} + \begin{pmatrix}0\\0\\1\\0\\0\end{pmatrix} + a_{50}$$

$$\sum_{l=1}^{L} \gamma_{j_l} = \gamma_3 + \gamma_2 + \gamma_1 \geq \gamma_n + \sum_{l=1}^{L-1} \gamma_{i_l + j_l - i_{l+1}} = \gamma_5 + \gamma_1 + \gamma_0$$

In the result, a generation slice of $\tilde{x}''^{1n}_{1n} = \min_{l} \tilde{x}'^{1n}_{i_l j_l}$ is added to $\tilde{x}'^{1n}_{1n}$ to get closer to the optimal schedule. $\tilde{x}''^{1n}_{13} = 0$ in the new solution. Furthermore, we know from the construction of the algorithm that $\tilde{x}''^{1n}_{13}$ will remain equal to zero for all future iterations.

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