Capacity remuneration mechanisms for electricity markets in transition

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Abstract

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The necessity to remunerate the provision of electrical capacity is intensively discussed among stakeholders in the electricity sector, as concerns about generation adequacy are growing due to an increasing share of intermittent renewable energies. Around the world and most recently in particular in Europe, different capacity remuneration mechanisms have already been implemented or are about to be introduced. These developments entail new challenges for regulators as well as market participants, yet it is still disputed whether capacity remuneration mechanisms are indeed needed.

In this dissertation, it is examined to which extent the expansion of renewable energies is linked to a decline in prices and restrained investments. It is shown that the drop in wholesale electricity prices in European markets is partly attributable to an increase in renewable production. However, the development of fuel prices, emission allowances prices, and the decommissioning of power plants are equal or even stronger factors. Notwithstanding, the profitable operation of state-of-the-art thermal power plants, i.e., combined cycle gas-fired units, remains difficult with the ongoing increase of renewable capacities, thus making it likely that the debate about capacity remuneration mechanisms will further intensify. Against this backdrop, an up-to-date overview of the debate on the necessity for capacity remuneration mechanisms is provided, and initial experiences with real-world implementations are discussed. In addition, the current state of research on capacity remuneration mechanisms is analyzed. While most studies agree that capacity remuneration mechanisms have certain advantages, for example, investment cycles can be dampened, and the adverse effects of the abuse of market power can be mitigated, no consensus is found on other issues, for example, the optimal design or cross-border effects.

In a case study for Germany, several potential market designs options are evaluated. The results show that an energy-only market has a short-term cost advantage, but long-term scarcity prices lead to similar system costs as in a central capacity market. Further, an energy-only market with a strategic reserve can incentivize investments, and ensure generation adequacy in a market with a high share of renewable energies. With a central capacity market, however, investment cycles are less likely to occur, and a predefined adequacy rate is easier to achieve. In a subsequent analysis, Switzerland is used as an illustrative case study for the assessment of cross-border effects of capacity remuneration mechanisms. The findings indicate that neighboring capacity remuneration mechanisms strongly influence domestic prices and investments. Due to the large-scale hydropower capacities in Switzerland, however, this does not result in a negative impact on generation adequacy. Thus, making the introduction of a local capacity remuneration mechanism optional.

On this basis of the obtained results, it is recommended that policy makers wanting to implement capacity remuneration mechanisms use considerable diligence. Capacity remuneration mechanisms, even though effective in increasing generation adequacy, are extremely difficult to design optimally, and a rash, poorly planned implementation may lead to more harm than good. In this context, further research is required to study the efficiency of capacity remuneration mechanisms oriented on real-world conditions, e.g., by integrating the behavior of learning, risk-averse market participants verified through studies or experiments.

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Bublitz, A., D. Keles, and W. Fichtner. 2017. "An analysis of the decline of electricity spot prices in Europe: Who is to blame?" *Energy Policy* 107, pages 323–336.

Chapter 5

Bublitz, A., D. Keles, F. Zimmermann, C. Fraunholz, and W. Fichtner. 2019. "A survey on electricity market design. Insights from theory and real-world implementations of capacity remuneration mechanisms." *Energy Economics* 80, pages 1059–1078.

Chapter 6

Bublitz, A., M. Genoese, and W. Fichtner. 2014. "An agent-based model of the German electricity market with short-time uncertainty factors." In: *11th International Conference on European Energy Market (EEM)*, pages 1–5.

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Keles, D., A. Bublitz, F. Zimmermann, M. Genoese, and W. Fichtner. 2016. "Analysis of design options for the electricity market. The German case." *Applied Energy* 183, pages 884–901.

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Bublitz, A., P. Ringler, M. Genoese, and W. Fichtner. 2015. "Agent-Based Simulation of Interconnected Wholesale Electricity Markets: An Application to the German and French Market Area." In: *Lecture Notes in Computer Science*. Edited by B. Duval, J. van den Herik, S. Loiseau, and J. Filipe. Volume 8946. 8946. Springer, pages 32–45.

Chapter 9

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List of Abbrevations

50Hertz	50Hertz Transmission GmbH.
ABSM	Agent-based simulation model.
ACER	Agency for the Cooperation of Energy Regulators.
AMES	Agent-based Modeling of Electricity Systems.
Amprion	Amprion GmbH.
API 2	Price index for hard coal (All Publications Index 2).
ARA	Antwerp, Rotterdam, Amsterdam.
BDEW	German Association of the Energy and Water Industries (German: Bundesverband der Energie- und Wasserwirtschaft).
BFE	Swiss Federal Office of Energy (German: Bundesamt für Energie).
BMU	Federal for Ministry Environment, Nature Conservation and Nuclear Safety (German: Bundesministerium für Umwelt, Naturschutz, Bau und Reaktorsicherheit).
BMWi	Federal Ministry for Economic Affairs and Energy (German: Bundesministerium für Wirtschaft und Energie).
BNetzA	German Federal Network Agency (German: Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen).

CCGT	Combined cycle gas turbine.
CHP	Combined heat and power.
CO_2	Carbon dioxide.
CONE	Cost of new entry.
CRM	Capacity remuneration mechanisms.
CSS	Clean spark spread.
CVaR	Conditional value at risk.
CWE	Central Western Europe.
DSM	Demand-side management.
EEG	Erneuerbare-Energien-Gesetz.
EEX	European Energy Exchange AG.
EFOM	Energy Flow Optimization Model.
EMLab	Energy Modelling Laboratory.
EnBW	Energie Baden-Württemberg AG.
ENTSO-E	European Network of Transmission System Operators.
EOM	Energy-only market.
E.ON	E.ON SE.
EPEX SPOT	European Power Exchange SE.

EU	European Union.
EUA	European Emission Allowances.
EU-ETS	European Union Emissions Trading System.
EUPHEMIA	Pan-European Hybrid Electricity Market Integration Algorithm.
F1PE	First Period European Carbon Future.
F2PE	Second Period European Carbon Future.
FEUA	European Carbon Future.
GASPOOL	GASPOOL Balancing Services GmbH.
ICT	Information and communication technology.
IEA	International Energy Agency.
IG BCE	Mining, Chemical, and Energy Industries Union (German: Industriegewerkschaft Bergbau, Chemie, Energie).
IKARUS	Instrumente für Klimagasreduktionsstrategien.
ISO-NE	ISO New England.
LOLE	Loss of load expectation.
LPX	Leipzig Power Exchange.
LSE	Load-serving entities.
MAE	Mean absolute error.

MAPE	Mean absolute percentage error.
MARKAL	Market Allocation.
MASCEM	Multiagent System That Simulates Competitive Electricity Markets.
MISO	Midcontinent ISO.
NCG	NetConnect Germany.
NetCONE	Net cost of new entry.
NPV	Net present value.
NTC	Net transfer capacity.
NYISO	New York ISO.
OCGT	Open cycle gas turbine.
OSeMOSYS	Open Source Energy Modeling System.
OTC	Over-the-counter.
PERSEUS	Programme Package for Emission Reduction Strategies in Energy Use and Supply.
PJM	PJM Interconnection LLC.
PRIMES	Price-Induced Market Equilibrium System.
PV	Photovoltaics.
RES	Renewable energy sources.

RMSE	Root-mean-square error.
RWE	RWE AG.
SD	Standard deviation.
SEPIA	Simulator for Electric Power Industry Agents.
SR	Strategic reserve.
TenneT	TenneT TSO GmbH.
TIMES	The Integrated MARKAL/EFOM System.
TransnetBW	TransnetBW GmbH.
TSO	Transmission system operator.
UK	United Kingdom of Great Britain and Northern Ireland.
US	United States of America.
Vattenfall	Vattenfall GmbH.
VoLL	Value of lost load.

Chapter 1
Motivation and introduction

European electricity markets are currently undergoing a phase of transition, which is characterized by three essential factors: first, the expansion of renewable energies, in particular, wind power and photovoltaics, second, a partial phase-out of nuclear energy, and third, the European market integration. These developments pose significant challenges that need to be mastered. In this process, three partly competing goals serve as a guiding principle: security of supply, affordability and environmental compatibility (BMWi, 2016a). Recently, a fourth goal has gained in importance: the social acceptance (Droste-Franke et al., 2015). Balancing these objectives is the basis for a country's prosperity and competitiveness, however, represents a tetralemma that includes complex links between public and private actors, governments and regulators, economic and social factors, national resources, environmental concerns, and individual behavior (World Energy Council, 2016).

Liberalization of the electricity market

Substantial structural changes have accompanied the development of electricity markets since the 1990s. At that time, markets in Europe underwent a profound transformation due to the incipient liberalization, whose process still continues until today. The so-called energy packages of the European Union formed the basis for this process, each a bundle of directives and sometimes also regulations that were subsequently implemented into national law by member states.

The first package consisted of two parts: A directive for the internal electricity market in 1996 (European Commission, 1997), which was followed by its counterpart for the gas market in 1998 (European Commission, 1998). These directives established rules for the third-party access in order to decouple the trading of electricity and gas from the physical transport on a particular network; thus, enabling competition despite existing network monopolies for the first time. Furthermore, large, industrial end consumers were now able to negotiate the purchase and sales of electricity. In 2003, the second energy package was adopted (European Commission, 2003a). It opened the gas and electricity market to new entrants. Also, all end-users including households were now able to freely choose their suppliers from a wider range of competitors. In 2009, the third energy package—consisting of three directives and two regulations—was passed with the aim of further liberalizing the internal electricity and gas market (European Commission, 2011c). The thereby newly opened possibility of non-discriminatory cross-border trade can be seen as a cornerstone of the implementation of the European internal energy market. In addition, the Agency for the Cooperation of Energy Regulators (ACER) was founded. Its task is to ensure the harmonization of regulatory frameworks through effective cooperation between national regulatory authorities, and if these are unable to reach an agreement, to take legally binding decisions on cross-border issues.

Restructuring the electricity market from regulated monopolies to a competitive market aims to improve system efficiency while simultaneously reducing system costs (Jamasb and Pollitt, 2005). However, competitive market structures could give rise to the exertion of market power by large electricity suppliers (Borenstein, 2000), and may not provide sufficient incentives for investment in new generation capacity (Vries, 2007). Therefore, the latest package of the European Commission named "Clean Energy for all Europeans" aims at the implementation of the Energy Union and includes, inter alia, the design of the electricity markets, the security of electricity supply and governance rules for the Energy Union (European Commission, 2018a).

Market coupling

The liberalization of the European energy markets has the overarching goal of creating a single internal energy market that enables barrier-free cross-border trade of electricity or primary energy sources such as oil or natural gas (European Commission, 2010b). An important step for the integration of the European electricity markets was the implementation of market coupling at the European electricity exchange (EPEX SPOT) for Central Western Europe (Benelux, France, and Germany) on November 9, 2010 (EPEX SPOT, 2016). Only three years later, market coupling was extended to Northwestern Europe. In this manner, generation capacities can be used more efficiently across borders, and market participants benefit from the resulting economic welfare gains (Weber, 2010). Whereas an identical price can be found in a single market area at all times, for coupled markets, this only applies if sufficient transmission capacity is available.

Nuclear phase-out

It is estimated that more than a third of the EU's nuclear reactors currently in operation reaches the end of their life cycle and are required to be shut down by 2025 (European Commission, 2018b). In addition, several European countries, e.g., Belgium, Germany, Spain, and Switzerland, have decided to phase out nuclear energy. The most prominent example, however, is Germany, where the phase-out was initially envisaged as early as 2000 with the objective of replacing nuclear energy by 2022 (Bundesregierung, 2002). Nonetheless, in October 2010, due to concerns about rising electricity prices, the phase-out date was postponed with the intention of using nuclear energy up to 2036 (Bundesregierung, 2010). In an unexpected twist, only five months later, the German government announced in reaction to the Fukushima Daiichi nuclear disaster a three-month moratorium for the eight oldest German nuclear power plants (Atom-Moratorium) (Nestle, 2012). While, due to technical revisions, three of the eight nuclear power plants had already been out of operation (Biblis B, Brunsbüttel, Krümmel), the remaining five power plants (Biblis A, Isar 1, Neckarwestheim 1, Philippsburg 1, Unterweser) were shut down temporarily. Finally, an amended version of the Atomic Energy Act came into force in August 2011, which provided for the definitive decommissioning of all eight plants and the gradual shutdown of all other German nuclear power plants by the end of 2022 (Bundesregierung, 2011a).

Expansion of fluctuating renewable energies

The decarbonization is one of the greatest global challenges of the 21st century (BMU, 2014) and to overcome it, the expansion of renewable energies is an indispensable part, which also brings about a profound change in the electricity system. Whereas some countries, for example, Switzerland, due to the existing natural resources and geographical conditions such as mountains, rivers or glaciers, renewable energies already had a share of 56.6 % in gross electricity consumption in 1990. At the same time in Germany, the share was only 3.4 %. Nonetheless, Germany has specified national energy policy goals, which stipulate a minimum share of renewable energies in electricity consumption of 40–45 % until 2025 (BMWi, 2015b) and 65 % until 2030 (BMWi, 2018a) in order to provide for a substantial reduction of national greenhouse gas emissions. These national targets are embedded in the long-term objective of the European Union (EU) of reducing greenhouse gas emissions by 80 to 95 % by 2050 compared to 1990 levels (European Commission, 2011a).

To achieve national targets, renewable energies are subsidized through various programs. The primary beneficiaries are photovoltaics and wind power, which already play a major role in today's electricity market and are expected to represent the largest share of electricity generation in the future (Haas et al., 2013; Smith Stegen and Seel, 2013). However, as the generation from photovoltaic and wind turbines is dependent on the stochastic nature of wind speed and solar radiation, deviations between the actual and forecasted generation must be continuously compensated by dispatchable generation capacities, storages, or interruptible loads to guarantee grid stability. Furthermore, these technologies have a considerable influence on the *average* residual load, i.e., the load that must be covered by conventional power plants. However, due to, for example, seasonal fluctuations or rare weather conditions only a weak influence on the *maximum* residual load can be observed. Photovoltaics and wind power have marginal costs close to zero and, by displacing more expensive thermal power plants, have a considerable influence on the hourly prices in the wholesale electricity market (see Figure 1.1), so that the prices can even become negative (Nicolosi, 2010) in case of an extreme feed-in of renewable energies.

Capacity remuneration mechanisms

As the continuous supply of electrical energy is critical for modern economies, security of supply has always been at the center of political attention. Despite its great importance in politics, its underlying definition can be described as rather blurred or elusive (Kruyt et al., 2009; Löschel et al., 2010).[1] Nonetheless, security of supply can be subdivided into the following components when considering the different temporal dimensions. In the short term, security of supply refers to the "ability of the electrical system to support unexpected disturbances such as electrical short circuits or unexpected loss of components of the system or sudden disconnection" (NERC, 1997). While in this context new serious challenges due to the transformations in the electricity system emerge, these are not the focus of this work. Instead, the long-term perspective is taken, which focuses on generation adequacy, i.e., "the ability of the electric system to supply the aggregate electrical demand and energy requirements of the end-use customers at all times, taking into account scheduled and reasonably

[1] An overview of the different definitions including their conceptual dimensions and limitations can be found in Winzer (2012).

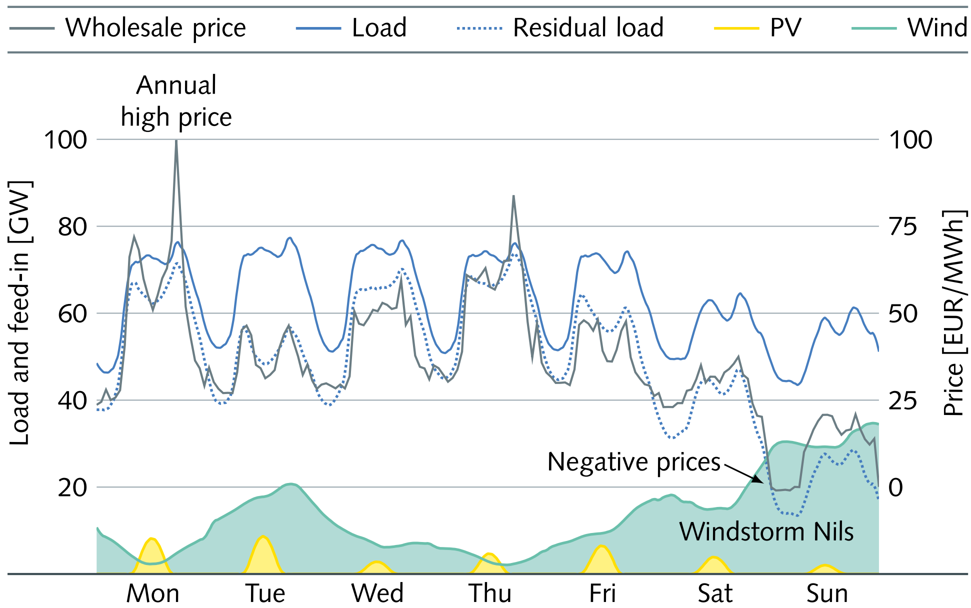

Figure 1.1 | Influence of the feed-in from fluctuating renewable energy sources on the German day-ahead market price. On Monday, November 23, 2015 at 5 p.m., the demand in the German day-ahead market could only be met to a very limited extent from fluctuating renewable energy sources. Therefore, the majority of the thermal capacities including the available peak load power plants were operated, which resulted in a market price of 99.77 EUR/MWh. However, when a low demand for electricity coincided with a high supply of wind turbines caused by a nationwide windstorm, wholesale prices became negative during the night from Saturday to Sunday. *Source:* EEX (2018a).

expected unscheduled outages of system elements" (North American Electric Reliability Council [NERC], 2018). However, in the aftermath of the liberalization process, generation adequacy is not the direct responsibility of a particular actor. Instead, liberalized markets should provide sufficient incentives for market participants to invest in technologies contributing to generation adequacy. In theory, even in the absence of active demand response, energy-only markets[2] generate efficient prices

[2] Energy-only in the sense that the provided energy is remunerated but not the amount of firm capacity a unit is able to supply. The latter could take place through different mechanisms, for example, capacity markets.

and, thus, lead to sufficient long-term investments guaranteeing the least-cost long-term system if several key assumptions are met (Caramanis et al., 1982; Oren, 2005; Schweppe et al., 1988; Stoft, 2002). However, in real-world markets, these assumptions do seldom hold, which can lead to underinvestment. Furthermore, there is a substantial risk that market power is exerted resulting in high prices or investment cycles occur in turn leading to inefficiency. To counteract this, the introduction of mechanisms remunerating generation capacity is discussed extensively. In particular, the rise of intermittent renewable energy sources or the market-related and political uncertainties, such as the phase-out of specific technologies, have rekindled the debate about capacity remuneration mechanisms and already led to their implementation in various European countries.

Challenges and models needed

To comprehensively analyze the possible development of the future energy system and to identify the most significant causal relations, the use of energy models has proven to be extremely valuable (Jebaraj and Iniyan, 2006). First steps were already taken following the oil price crises in the 1970s when the development of quantitative energy models was commenced in view of an imminent oil shortage in order to investigate possible effects on the security of energy supply and the increased use of energy-saving technologies (Huntington et al., 1982). Due to the continually evolving political and market economy environment, the requirements for energy modeling have significantly changed, and, as a result, new research areas have emerged (Pfenninger et al., 2014). In particular, due to market liberalization and the central role of the various market players involved, methods must be developed to model a complex system taking into account the perspective of the players, their decision-making processes, and their interactions (Santos et al., 2015). In this way, for example, energy policy measures do not have to be specified in the form of exogenous assumptions, but can be implemented as explicit instruments and thus researched under realistic conditions.

1.1 Thesis structure

In order to contribute to a deeper understanding of the development of the electricity system and in particular the role of capacity remuneration mechanisms, the central objective of this work is to develop and apply methodological approaches for investigating the impact of renewable energies on the electricity market as well as the effect and cross-border influence of capacity remuneration mechanisms. This requires an explicit representation of techno-economic restrictions, existing marketplaces, individual market players, available generation as well as transmission capacities.

Throughout this work, a focus is placed on the German electricity market, the largest electricity market in Europe. Germany shows by far the largest expansion of wind energy and photovoltaics in Europe (EurObserv'ER, 2017; European Wind Energy Association [EWEA], 2017) and, in combination with the phase-out of nuclear power, is undergoing a dynamic transition phase, which is still to come for many other countries. As a result, the German market is particularly suitable for investigating the effects of capacity remuneration mechanisms both domestically and across borders, e.g., in Switzerland. To address the economic concepts of capacity remuneration mechanisms as well as the required techno-economic models and the framework of the German electricity sector, this work is divided into the following chapters.

In *Chapter 2*, the main techno-economic framework conditions of the German electricity sector are described, whereby the results of this work can be interpreted in an overarching context. To this end, the first sections of the chapter deal with the characteristics of the German electricity market, the different long-term and short-term wholesale electricity markets and their interrelationship. In the next sections, the most significant economic and regulatory developments in the electricity sector of the last years, e.g., the promotion and expansion of renewable energies or plans for implementing capacity remuneration mechanisms are analyzed and discussed.

In *Chapter 3*, light is shed on techno-economic electricity market models, which allow a deeper understanding of the interrelationships in electricity markets. First, a description of the various possible model classifications, including their fundamental characteristics, is given. Subsequently, a comparison of the individual model types is carried out where model-specific strengths and shortcomings are discussed. In a next step, for each model type, the suitability for the analysis in this work is examined, and finally, the need for further research efforts in view of the ongoing transformation of electricity systems is addressed.

In *Chapter 4*, a common rationale for capacity remuneration mechanisms is examined in which the expansion of renewable energies is directly associated with a decline in electricity prices and insufficient investment. For this purpose, the largest electricity market in Europe, i.e., the German electricity market, is a suitable example, as it shows a remarkable expansion of renewable energies parallel to a progressive price decline from about 51 to 31 EUR/MWh in the period from 2011 to 2015. By applying an agent-based model as well as a regression approach with either static or separate time-varying coefficients, the contribution of the different price drivers, e.g., fuel prices, emission allowances prices, or decommissions of power plants, is broken down.

In *Chapter 5*, an up-to-date overview of the debate on the necessity for capacity remuneration mechanisms is provided. This survey also covers the underlying peculiarities of electricity markets that form the basis for the unique regulatory framework in place in most markets. Furthermore, the status of the implementation of capacity remuneration mechanisms in Europe is presented, and initial experiences are discussed. In addition, the current state of research on capacity remuneration mechanisms is analyzed, e.g., with regard to cross-border effects, investment cycles or a high share of intermittent renewables. Finally, shortcomings of the existing research works are identified, and unresolved issues are highlighted.

In *Chapter 6*, an agent-based model for the German wholesale electricity market is presented that accounts for short-time uncertainty factors, such as power plant outages or fluctuating renewable energy sources. In this model, generation companies are represented by agents that submit bids into the market based on variable costs, start-up costs and ramping restrictions of their generation capacities. In order to validate the model, an assessment is carried out in which historical market results are compared with simulated results.

In *Chapter 7*, it is analyzed whether in Germany capacity remuneration mechanisms are required or whether the current market design is able to incentivize sufficient investments in dispatchable capacity. Furthermore, the role of demand-side management in increasing generation adequacy is examined, whose effect is twofold: In the short term, demand fluctuations can be reduced by dispatching flexible loads with relatively low marginal costs often below the generation costs of existing thermal capacities. In the long term, sheddable loads can enhance generation adequacy in extreme situations while simultaneously triggering price peaks at several hundred EUR/MWh allowing investors to refinance investments in the presence of a relatively flat merit-order curve dominated by renewable energy sources with marginal costs close to zero.

In *Chapter 8*, in accordance with the current European market framework, market coupling is implemented for different market areas with limited interconnection capacities. First, market participants submit their bids to the local power exchanges. Then, a central market operator takes over all processes related to the coupling. For that purpose, the operator receives all day-ahead bids from the local power exchanges. The market coupling itself can be formulated as an optimization problem with the objective to maximize social welfare. In a case study, results for the market coupling of the German and French wholesale electricity market are presented.

In *Chapter 9*, Switzerland is chosen for a real-world case study on cross-border effects of capacity remuneration mechanisms. As the Swiss electricity market is tightly connected to the large neighboring markets of France, Germany, and Italy, it is well suited to illustrate the impact of large neighboring markets on a small national electricity market. Moreover, in the neighboring countries, the implementation of capacity remuneration mechanisms has already been completed or is expected in the near future, so that close-to-reality results can be attained and studied.

Chapter 2
Framework of the German electricity sector

In this chapter, the main techno-economic and regulatory framework conditions of the German electricity sector are described. First, the characteristics of the German electricity market, the different long-term and short-term wholesale electricity markets and their interrelationship are examined. Subsequently, the most significant economic and regulatory developments in the electricity sector of the last years are analyzed and discussed, which have driven the debate on generation adequacy and capacity remuneration mechanisms either directly—e.g., the implementation of the German capacity reserve—or indirectly by strongly influencing market prices or the profitability of dispatchable generation capacity, such as the expansion of renewable energy or the development of fuel prices.

2.1 The German wholesale electricity market

Due to its central location on the European continent and in combination with its size as Europe's largest electricity market, the German electricity market is of particular significance, which is reflected in its considerable cross-border influence, especially on its smaller neighbors. This section provides a brief overview of the current state of the German electricity market, examining among other things the various market segments, i.e., the derivatives, day-ahead, and intraday market, with

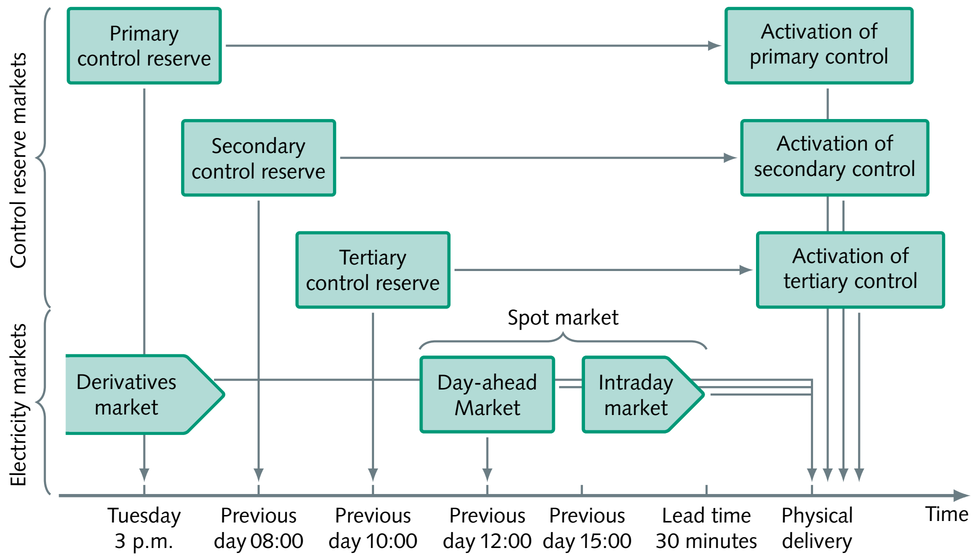

Figure 2.1 | Chronological sequence of energy and reserve markets. In Germany, electricity can be traded years in advance on the derivatives market and until shortly before physical delivery on the intraday market. For the latter, the physical gate closure is the limiting factor that for trades within a control zone and across control zones occurs 5 and 30 minutes before physical delivery. Alongside the ongoing electricity trading, transmission grid operators cover their demand for balancing power via weekly or daily auctions. *Sources:* 50Hertz Transmission et al. (2017); EEX (2018a).

their characteristic features, marketplaces, products, and participants. An overview of the chronological sequence and the interaction of the individual elements of the German electricity market can be found in Figure 2.1.

2.1.1 Marketplaces

An important milestone after the liberalization of the electricity sector in Europe was the creation of energy exchanges. The most important trading center for Germany is the Leipzig-based European Energy Exchange AG (EEX), which was established in late 2001 by the merger of the Leipzig Power Exchange (LPX) and the former European Energy Exchange based in Frankfurt (EEX, 2018a). Since then, it has developed from a national electricity exchange to a multi-commodity trading platform, where energy and energy-related products such as electricity, natural gas, hard coal, and emission allowances are traded on different European derivatives and spot markets. Due to its high liquidity, the EEX is widely considered as the reference point for the German electricity market (Viehmann, 2011).

Similar to financial products, electricity can be traded either in organized markets or over-the-counter (OTC). The main difference between exchange-traded and OTC contracts is that the former are standardized and their regulation is approved by a competent body (Cartea and Villaplana, 2014). In the case of over-the-counter trading, the terms of a transaction are only bilaterally agreed upon by the trading partners without the involvement of a central authority. Even though off-exchange transactions can be performed directly between two parties, it is still possible to register them on a stock exchange, e.g., to be protected against counterparty risk.

Central trading on a power exchange has the advantages of increasing market transparency, providing valuable price information for other market participants and thus reducing transaction costs (Weidlich, 2008). OTC trading, on the other side, offers a high degree of flexibility allowing, for example, custom defined load profiles to be hedged. Typically, the specific contractual obligations are kept confidential, and only the over-the-counter trading volume registered on a stock exchange is publicly known.

2.1.2 Derivatives market

On the derivatives market, products are traded for which a period of several days but often weeks, months or years lies between the signing and settlement of a contract. These contracts can be categorized into conditional and unconditional transactions (Deng and Oren, 2006). In the case of a conditional transaction, e.g., an option, a contracting party has the right, but not the obligation, to enforce the fulfillment of the contract. In the case of an unconditional transaction, e.g., a futures contract, both contracting parties have entered a binding obligation. Thus, the contract is always

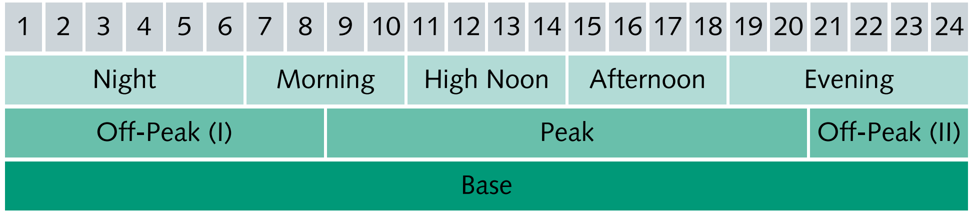

Figure 2.2 | Standardized electricity contracts. For each derivate contract at the EEX, there is a differentiation between base load, i.e., delivery takes place for every hour of the indicated delivery period of the contract, e.g., an entire year, or peak load, which includes delivery from 08.00 to 20.00 hours for all specified days. For the day-ahead market at the European Power Exchange SE (EPEX SPOT), there are also other products, e.g., off-peak or depending on the time of day, e.g., night or morning. *Sources:* EEX (2018a); EPEX SPOT (2015).

executed. The contract can usually be fulfilled physically, i.e., by supplying electricity, or financially by making a compensation payment.

In order to avoid a lack of liquidity for individual products, selected derivatives contracts are available on the market. At the EEX, for example, annual contracts, i.e., contracts with a delivery period of one year, can be traded for the next 6 years. Contracts with a shorter delivery period, e.g., quarterly, monthly or weekly contracts, can be traded for the next 11 quarters, next 9 months or next 4 weeks (EEX, 2018a). For each product traded, usually different characteristics exist, e.g., the Base Week Future or the Peak Week Future (Figure 2.2). The most prominent product for the German market is the Phelix Future[1], whose underlying is the average electricity price of the German/Austrian or since recently only the German day-ahead market determined by the EEX (EEX, 2015).

First and foremost, the derivatives market can be considered as an instrument for hedging against price risks of which extensive use is made (Cartea and Villaplana,

[0] The churn rate in a specific market area is defined as the ratio of the volume of all trades to the total demand, i.e., electricity consumption. This figure can be used to draw conclusions about the liquidity of a market and the quality of its price signals (European Commission, 2014a). However, there is no consensus on the level at which sufficient market liquidity exists.

[1] Phelix refers to *Physical Electricity Index* as the underlying values for the index are linked to a physical supply of electricity, a difference to financial contracts where only a cash settlement is made.

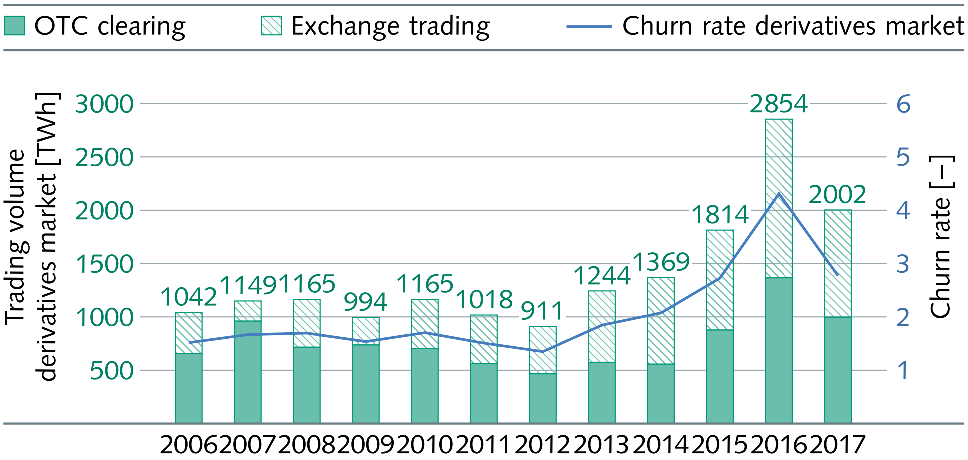

Figure 2.3 | Annual trading volumes of derivatives contracts for the German/Austrian market area. The annual trading volume remained relatively constant from 2006–2011. Afterward, mainly due to the increase in trading of standardized contracts, the volume has been rising steadily. The by far most frequently traded standardized contract is the "Phelix Base Year Future." The large trading volumes result in the fact that for the entire period shown the churn rate[2] is greater than one, i.e., more than the total electricity consumption is traded per year. *Sources:* AG Energiebilanzen e. V. (2018); E-Control (2016); EEX (2018a).

2014). This can be demonstrated by the fact that the derivatives market at the EEX has significantly larger trading volumes than the day-ahead and intraday market combined (see Figures 2.3 and 2.4). Most notably, electricity suppliers are enabled to optimize their medium- to long-term portfolio by selling the future power generation of their power plants in advance to arbitrage traders, speculators or other electricity suppliers.

As electrical energy cannot be stored economically in large quantities, the price of an electricity futures transaction cannot be expressed—as it is otherwise common with physical commodities (*cost of carry*)—by the current spot price and the storage costs (Weron, 2000). Rather, the price of an electricity forward contract reflects the expected spot price within the delivery period plus or minus a risk premium (Huisman and Kilic, 2012).

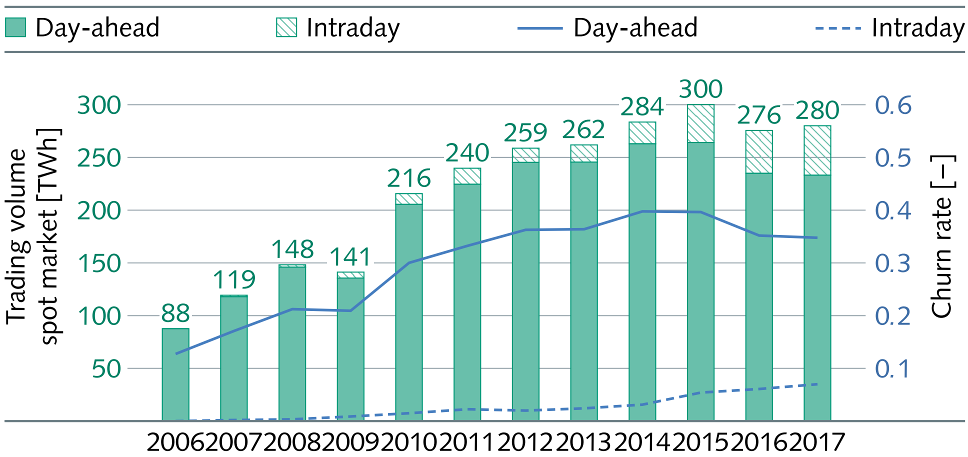

Figure 2.4 | Annual trading volumes of the day-ahead and intraday market for the German/Austrian market area. The intraday market, which was introduced in 2006, is steadily gaining in importance due to the increase in fluctuating renewable energies. By contrast, developments in the day-ahead market are more volatile; however, the most striking feature is the sharp increase in volume in 2010, which is related to the fact that by the amendment of the Erneuerbare-Energien-Gesetz (EEG), transmission system operators were obligated to offer the electricity generation from renewable energies in the day-ahead or intraday market (Bundesregierung, 2009; EEX, 2010). Despite the growth in the day-ahead and intraday market, which is also visible in the increased churn rate, the total trading volume of both markets is still slightly less than half of the combined annual electricity consumption in Austria and Germany. *Sources:* AG Energiebilanzen e. V. (2018); E-Control (2016); EEX (2018a).

2.1.3 Day-ahead market

The day-ahead market refers to the market, on which short-term orders with delivery on the following day can be placed, e.g., the EPEX SPOT in Paris, where trading takes place within the framework of a single auction or, in rare cases, a second uniform price auction. On the day-ahead market, not only peak load or base load products but also individual hours can be traded. Currently, around 200 different companies are registered for trading on the German/Austrian day-ahead market (EPEX SPOT, 2018a), which together provide for a high level of liquidity (Figure 2.4). A large part of the market participants are utilities who optimize their portfolio, which consists of their available generation capacities and the supply contracts with their customers. Other participants are larger industrial companies, who try to purchase electricity at the best price, and pure traders, e.g., banks and financial service providers, that seek to exploit price differences and take speculative positions. Furthermore, to offer the expected electricity feed-in from renewable energy sources or to compensate their grid losses, transmission system operators are participating in the market. Although the number of participants is comparable to the derivatives market, the total volumes traded on the day-ahead market are significantly lower.

First and second auction

Until 12:00 a.m. on the day before physical delivery, bids can be submitted to the EPEX SPOT electronic trading platform for every 24 hours of the next day[3]. At this point, most of the information required to optimize the power plant dispatch for the next day is already available (Ströbele et al., 2012). To all submitted bids, the following restrictions apply: The offered price must be within the price range of −500 to 3000 EUR/MWh, whereby the minimum price increment equals 0.10 EUR/MWh. In addition, the traded volume must be equal to or greater than 0.10 MWh (EPEX SPOT, 2017b).

After all bids have been placed, the outcome is calculated by a market clearing algorithm commonly known as the Pan-European Hybrid Electricity Market Integration Algorithm (EUPHEMIA), and for each hour an identical price is assigned to all accepted bids in each market (EPEX SPOT, 2016). The result of this uniform-price auction is not only relevant for the market participants at the day-ahead market, but also for derivatives traders as the base or peak day-ahead price is the underlying asset price of a large number of derivatives contracts (Frontier Economics, 2011). Furthermore, the day-ahead price is used to calculate the market premium for renewable energies (Bundesregierung, 2014). Several statistical key figures of the historical electricity

[3] During the transition from summertime to wintertime, 25, vice versa, 23 hours are traded.

Table 2.1 | Statistical figures of the day-ahead auction results at the EEX for the German/Austrian market area. Between 2005 and 2016, electricity prices show a wide range and considerable deviations from the annual average. At first, the price development does not indicate a long-term trend, but prices have been steadily decreasing from 2011 to 2016. Whereas extreme maximum values of more than 500.00 EUR/MWh were observed in the first years, the market stabilized thereafter. This is also reflected in the standard deviation, which from 2009 stayed below 20.00 EUR/MWh. *Source:* EEX (2018a).

Year	Arith. mean* [EUR/MWh]	Standard deviation [EUR/MWh]	Skew [–]	Minimum [EUR/MWh]	Maximum [EUR/MWh]
2005	45.98	27.22	4.88	0.00†	500.04
2006	50.79	49.42	25.05	0.00†	2436.63
2007	37.99	30.35	6.88	0.00†	821.90
2008	65.76	28.65	1.17	−101.52	494.26
2009	38.85	19.41	−3.23	−500.02	182.05
2010	44.49	13.97	−0.07	−20.45	131.79
2011	51.12	13.60	−0.64	−36.82	117.49
2012	42.60	18.68	−2.64	−221.99	210.00
2013	37.78	16.46	0.09	−100.03	130.27
2014	32.76	12.77	−0.27	−65.03	87.97
2015	31.63	12.66	−0.31	−79.94	99.77
2016	28.98	12.48	−0.47	−130.09	104.96
2017	34.19	17.66	0.02	−83.06	163.52

* The arithmetic mean refers to the non-weighted hourly prices.
† At the EEX, negative electricity prices were introduced in September 2008 at the request of the market participants; previously, the lower price limit was 0 EUR/MWh (EEX, 2008).

prices at the day-ahead-market for the German/Austrian market area can be found in Table 2.1.

According to the current rules of the EPEX SPOT, a second auction can be held if the market is in imbalance or if the first auction leads to a price that can be considered abnormal in view of the current market situation, i.e., the price of one or more hours is significantly different from the results of a similar day or the other hours of the current day (EPEX SPOT, 2017b). Whether such a case is present, is investigated if the price falls below −150 EUR/MWh or exceeds 1500 EUR/MWh for at least one hour. If a second auction is called, it will take place immediately after the first so that the final auction results can be published from 12:42 p.m. onward.

In addition to hourly bids, also block bids can be submitted (Biskas et al., 2014). A block bid—i.e., a bid for a certain number of consecutive hours within a day—is subject to an all-or-nothing condition, meaning that it either is accepted for all hours or rejected altogether. Thereby, market participants can better express their preferences for the complementary characteristics of electricity generation in successive periods, which among other things are due to the once occurring start-up costs of power plants (Reguant, 2014). Therefore, block bids can be seen as a specific pairing of hourly bids, which make it possible to deliver an average price over a pre-defined period of time. As this ensures that all incurred costs are covered—whereas hourly bids are subject to the risk that individual bids might be rejected and therefore partial costs are not covered—a lower average price for the delivery in consecutive hours can be offered.

In addition to plain block bids, also two types of smart block bids can be traded: linked and exclusive block bids (EPEX SPOT, 2015). Linked block bids allow to take into account the financial and technical constraints of market participants by offering, for example, start-up costs of a power plant in the first block and fuel costs in a further block. In addition, energy storages can profit from linked block bids, e.g., by only submitting a sell bid for a peak load hour if previously an ask bid has been accepted in an off-peak phase. Exclusive block bids, on the other hand, can be used to pursue different trading strategies for a power plant for the same delivery day (EPEX SPOT, 2014a). For example, a base load generation profile may be offered at a lower price, and a peak load profile at a higher price, but only one of the offers is allowed to be executed.

Although block bids offer market participants a wide range of possibilities to better reflect their financial and technical constraints, their use is currently still restricted.

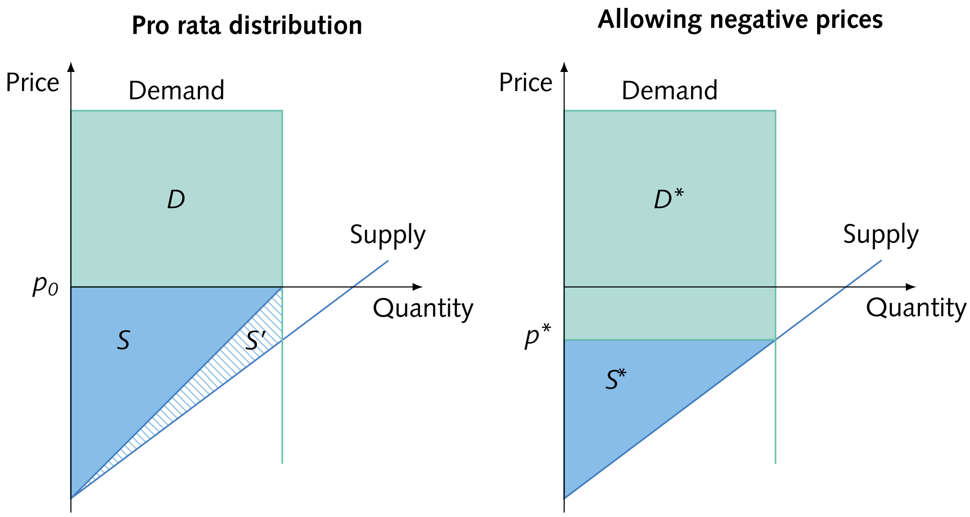

Figure 2.5 | Welfare effect of negative prices. The admission of negative prices increases economic welfare, as an efficient allocation is possible, and the welfare loss caused by the price limit p_0 in the pro rata allocation characterized by the area S' can be avoided. In addition, the ratio of consumer and producer surplus is changing. Although in the considered hour the consumer surplus rises from D to D^*, in the same period, the producer surplus decreases from S to S^*. Nevertheless, the allowance of negative prices also brings advantages for producers, as the welfare gain, which is generated in the following hours—however not depicted here—must be accounted for in the evaluation of the total effects. *Source:* Viehmann and Sämisch (2009).

For example at the EPEX SPOT, the maximum volume per block bid is 600 MWh, and for each day a maximum of 100 block bids per trading account can be submitted (EPEX SPOT, 2015). This is related to the fact that block bids substantially increase the complexity of market clearing algorithms (Madani and van Vyve, 2015). If, for example, only block bids with a static bid quantity were submitted, due to the all-or-nothing condition, there would only be a market equilibrium when the accumulated ask and sell volumes exactly match.

Negative prices

Since September 4, 2008, it has been possible to place bids with negative prices for the day-ahead market at the EEX. Prior to this, in the event of an oversupply, a pro rata allocation was made, in which each supplier could sell only part of its bid volume, which led to inefficiencies (see Figure 2.5). In addition to avoiding inefficient auction results, negative prices have the benefit of providing an incentive to invest in flexible system components and storage options (Brandstätt et al., 2011).

Although negative prices seem counterintuitive at first glance, due to the special properties of the good electricity, negative prices are economically reasonable (Brandstätt et al., 2011). For technical reasons, electricity can only be stored in limited quantities and, in order not to compromise grid stability, injections and withdrawals must always be in equilibrium. However, the demand is comparatively inelastic in the short term—only parts of the energy-intensive industry react to price signals, whereas the majority of household consumers do not adjust their behavior (Andor et al., 2010). Thus, in the event of an oversupply, the electricity generation must be reduced, which becomes increasingly complicated in particular in the case of a low demand.

Under current German law, transmission system operators are obliged to prioritize the feed-in of renewable energy sources and sell them directly, e.g., via energy exchanges, regardless of the current market prices (Bundesregierung, 2000). Recently built capacities must be marketed directly by the owner or an intermediary (Bundesregierung, 2014). These capacities, as well as all the capacities that deliberately opted for direct marketing, have an income depending on the price at which they sold their energy and receive an individual market premium retroactively. However, this market premium is suspended for all periods during which prices remain continuously negative for at least 6 hours. Thus, in contrast to capacities that receive a fixed feed-in tariff, all directly marketed capacities have an incentive to react to

Table 2.2 | Negative historical electricity prices on the day-ahead market for the German/Austrian market area. For the years 2010–2017, the corresponding two hours, in which the lowest prices were observed, are shown. Up to and including 2012, negative price peaks were often found during winter nights. However, due to the expansion of photovoltaics, in the following years, extreme negative prices increasingly occurred in warmer seasons when photovoltaics and wind power plants generated large quantities of electricity simultaneously. *Sources:* EEX (2018a); ENTSO-E (2018b).

Date	Time	Day	Day-ahead price [EUR/MWh]	PV [GWh]	Wind [GWh]	Load [GWh]	Residual load* [GWh]
03/01/2010	03:00	Mon	−18.1	0.0	13.9	49.4	35.5
12/12/2010	02:00	Sun	−20.5	0.0	19.4	51.5	32.1
01/01/2011	07:00	Sat	−34.2	0.0	12.3	37.1	24.8
02/04/2011	23:00	Fri	−36.8	0.0	22.6	56.7	34.1
12/25/2012	02:00	Tue	−222.0	0.0	18.6	30.6	12.0
12/25/2012	03:00	Tue	−221.9	0.0	17.8	30.4	12.6
06/16/2013	14:00	Sun	−100.0	20.0	8.7	41.8	13.1
06/16/2013	15:00	Sun	−100.0	18.3	8.0	40.6	14.3
05/11/2014	14:00	Sun	−65.0	14.0	20.5	49.8	15.3
05/11/2014	15:00	Sun	−65.0	12.9	20.0	48.5	15.6
04/12/2015	13:00	Sun	−65.1	21.1	12.0	49.6	16.5
04/12/2015	14:00	Sun	−79.9	20.1	12.9	47.8	14.8
05/08/2016	13:00	Sun	−100.1	26.8	18.0	46.9	2.1
05/08/2016	14:00	Sun	−130.1	25.3	18.5	44.4	0.7
10/29/2017	02:00	Sun	−83.0	0.0	35.9	51.2	15.3
10/29/2017	04:00	Sun	−83.0	0.0	34.7	52.1	17.4

* To calculate the residual load, the feed-in of photovoltaics and wind energy was subtracted from the total load, but other factors, such as run-of-river hydroelectricity, were not included.

persistent negative or to extreme negative prices that exceed their market premium[4]. The prioritization of renewable energies is a decisive factor for the occurrence of negative prices and ensures that primarily thermal power plants have to adapt their

[4] Even if in theory the plant operators of directly marketed renewable energies should react flexibly to negative prices, according to Energy Brainpool (2016) in a single hour on May 8, 2016, a cost saving of up to 800 000 EUR could have been achieved if renewable plant operators had simply reduced their feed-in.

generation. An examination of the most negative prices of recent years reveals that these occurred in combination with a high feed-in from photovoltaic and wind power plants (Table 2.2).

For technical or economic reasons power plants want to avoid to lower their generation and are willing to accept low or even negative prices (Genoese et al., 2010; Vos, 2015). Technical restrictions such as a slow load change speed or minimal downtimes prevent a power plant from only running in those hours in which a positive contribution margin can be achieved. For example, after a power plant is partially or fully shut down, it cannot immediately be operated at full capacity, even if a high market price is expected in the following hours. Therefore, its operator is willing to accept losses on a temporary basis, which, however, will be offset by subsequent earnings. Furthermore, some power plants must remain in operation due to contractual obligations (must-run capacities), for example, capacities that provide negative balancing power or run-of-river power plants (Böttger et al., 2015). Furthermore, in some combined heat and power plants, the electricity generated is regarded as a by-product, and the supply of heat for industrial processes or the heating of buildings is the main source of income, and financial penalties are imposed if the heat supply is interrupted (Mitra et al., 2013).

2.1.4 Intraday market

The intraday market can be defined as the market that operates between the day-ahead market and the physical gate closure, i.e., the point in time after which a change to the schedules submitted to the system operator is no longer permitted (Weber, 2010). Above all, the market is used by market participants to adapt their schedule to deviations that were not foreseeable when submitting their bids at 12:00 a.m. on the previous day. Whereas the volumes traded on the intraday market are quite small compared to, e.g., the day-ahead or derivatives markets, trading has grown in importance in recent years (Figure 2.4). Due to the short time interval between the day-ahead and intraday market, market prices closely resemble each other (Tables 2.1 and 2.3).

Trading on the intraday market is possible until the schedules transmitted to the transmission system operator can no longer be changed. In 2011, the lead time between the closure of the intraday market and physical delivery was reduced from 75 minutes to 45 minutes (EPEX SPOT, 2011b). In 2015, technical changes allowed for a further reduction to 30 minutes[5]. Since 2017, trading within an individual control area is permitted up to 5 minutes before delivery (EPEX SPOT, 2017c), providing market participants with the ability to facilitate their portfolio management by responding to short-term changes in electricity production—particularly as a result of the growing share of renewable energies—or consumption.

At the intraday market, continuous trading takes place. This means new orders can be submitted from 4:00 p.m. of the previous day until gate closure. Whenever a corresponding counterpart is found, a trade is carried out. Thereby, market participants are able to constantly obtain new information (Selasinsky, 2016). In addition to single hours, also standardized blocks are traded in the intraday market. The trading of quarter-hourly contracts started in December 2011, which, for example, is particularly advantageous to market the generation from photovoltaics, which has strong hourly but often also well-predictable variations. Furthermore, orders can be subject to an execution condition, such as "fill or kill," which ensures that a bid is either executed immediately or entirely canceled. The minimum contract size for each bid is 0.10 MW and the minimum price increment 0.10 EUR/MWh. Compared to the day-ahead market, the price range of orders with −9999 to −9999 EUR/MWh is noticeably wider (EPEX SPOT, 2017a).

In December 2014, in addition to continuous trading, a uniform price auction was introduced to increase the liquidity of the market (EPEX SPOT, 2014b), in which all quarter hours of the next day are eligible for trading. The auction opens the intraday

[5] The lead time of 30 minutes refers only to trades within Germany, whereas the lead time for cross-border trade, for example, between Germany and France, is still 60 minutes.

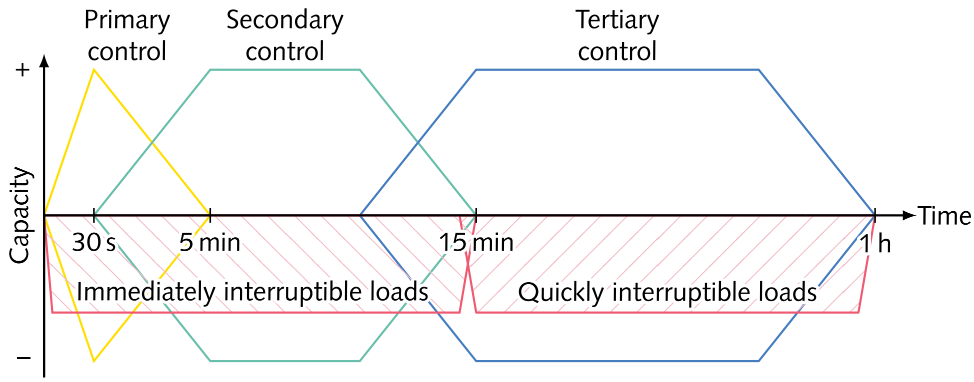

Figure 2.6 | Chronological sequence of the usage of the operating reserves and interruptible loads. Transmission system operators have three different reserves at their disposal, which can be utilized successively if a power imbalance occurs. Additionally, since the amendment to the Energy Industry Act of 20 December 2012, quickly or immediately interruptible loads can be accessed if negative balancing power is required.

market[6] for trading on the following day as it takes place daily at 3:00 p.m. and provides an initial price signal for the continuous trading that commences one hour later at 4:00 p.m. The market clearing is also carried out by the EUPHEMIA algorithm. However, as the auction is only conducted for the German market area, no market coupling occurs.

2.1.5 Markets for control reserve

Although there is only one single market area in Germany, it is divided into four different control areas, each of which falls under the responsibility of one of the four transmission system operators: 50Hertz Transmission GmbH (50Hertz), Amprion GmbH (Amprion), TransnetBW GmbH (TransnetBW) and TenneT TSO GmbH (TenneT). The primary purpose of a transmission system operator is to ensure a safe network operation at all times (Bundesregierung, 2005). However, this may be at risk

[6] The term intraday market may lead to confusion as transactions with delivery on the current day and the next day are permitted on this market. In addition, the distinction to the day-ahead market seems arbitrary as the daily auctions at 12.00 a.m. and 3.00 p.m. both with the delivery on the next day belong once to the day-ahead market and once to the intraday market.

Table 2.3 | Statistical figures of the continuous intraday prices at the EEX for the German/Austrian market area. The volume-weighted average hourly prices of the intraday market show a similar development to the day-ahead market, which can be attributed to the short time lag between these two markets. However, it is noticeable that the average prices on the intraday market show a higher deviation and the annual minimum and maximum reaches extremer values. For individual transactions, the extremes are even considerably higher, and occasionally prices reach four-digit values. One explanation is that the continuous trading in the intraday market sometimes requires very short lead times and only few capacities possess the necessary flexibility. *Source:* EEX (2018a).

Year	Arith. mean* [EUR/MWh]	Standard deviation [EUR/MWh]	Skew [–]	Minimum [EUR/MWh]	Maximum [EUR/MWh]
2006†	51.53	19.94	0.13	0.50	150.64
2007	41.26	29.65	4.34	0.00	601.14
2008	65.14	28.32	0.90	–22.65	389.79
2009	39.04	24.96	–6.32	–648.62	173.72
2010	45.62	16.56	0.16	–62.62	180.07
2011	51.22	15.47	–1.23	–139.07	156.22
2012	43.78	19.39	–0.41	–254.09	265.30
2013	38.58	17.48	0.34	–83.25	155.61
2014‡	33.14	13.39	0.10	–53.65	125.12
2015‡	31.71	14.55	–0.70	–89.14	167.27
2016‡	29.25	13.69	–0.88	–184.89	134.01
2017‡	35.54	23.21	0.43	–70.10	179.69

* The arithmetic mean refers to the volume-weighted hourly prices.
† As the intraday market at the EEX was opened on September 25, 2006, the results for the year 2006 are only partially comparable with the later years for which all hourly prices are available.
‡ The results of the 15-minute auction introduced in December 2014 are not included in the statistical figures.

if deviations occur between the expected and actual generation or consumption. This can be caused, for example, by the unexpected non-usability of thermal power plants or forecast errors for the electrical load as well as the generation from renewable energy sources (Müsgens et al., 2014). In order to respond to these deviations, a transmission system operator has various options at its disposal: the primary control, the secondary control, the tertiary control reserve, and more recently immediately and quickly interruptible loads (50Hertz Transmission et al., 2017). To keep the system frequency always near its target of 50 Hz and to eliminate regional deviations, the use of the various operating reserves must be coordinated in terms of both the extent and timing (Figure 2.6). Since 2010, the use of balancing power has also been coordinated across the control areas by first settling the differences between the individual control areas and only balancing the remaining difference (Ströbele et al., 2012). Thereby, inefficiencies can be avoided and costs reduced.

Deviations from the declared schedules can be caused both by the supply and demand side. If these deviations result in a low supply of electrical energy or vice versa in an oversupply, the target frequency of 50 Hertz is undercut or exceeded respectively (Erdmann and Zweifel, 2008). If an unexpectedly high supply meets a low demand, negative balancing power is needed, i.e., the feed-in of the active power generation units must be reduced. Vice versa, if a negative imbalance occurs, positive balancing power is required, i.e., a power plant has to increase its generation or, alternatively, immediately and quickly interruptible loads have to be activated.

In order to participate as a provider in a tender for balancing power, a framework contract must first be signed with the responsible transmission system operator. For this, it is necessary that the provider has proven by means of a successfully completed prequalification that he fulfills all necessary technical requirements and that his disposable capacity exceeds the respective minimum bid size for the different operating reserves. The three different operating reserves are described in more detail in the following sections, and a comparative overview can be found in Table 2.4.

Primary control reserve

The first measure to achieve a prompt stabilization of the system frequency after a disturbance event is the activation of the primary control reserve, which is carried out automatically by the decentralized control devices of the units involved, mainly the speed controllers of power plants. This can be accomplished almost without any time delay, and the system frequency is stabilized within a few seconds (Galiana et al., 2005).

The necessary size of the primary control reserve is determined annually in consultation with the European transmission system operators, whereby a total quantity of 3000 MW is currently being provided for continental Europe (ENTSO-E, 2009). This capacity is then distributed among the transmission system operators in relation to the annual electricity feed-in (Fleer and Stenzel, 2016). In the last years, the total capacity required for the German control areas varied between 500 to 800 MW (50Hertz Transmission et al., 2017). Between 2010 and 2015, the annual costs for the provision of primary control power amounted to approximately 100 million EUR (BNetzA, 2014, 2015, 2016b).

The primary control reserve is tendered weekly, whereby each provider must provide positive and negative capacity simultaneously. As a result, primarily power plants that are used to cover the base load also provide primary control power. However, the market for primary control power has recently become attractive for large battery storages, whose prices have fallen sharply. Battery storages also have the advantage of higher dynamics and a more precise response without representing a must-run[7] capacity (Stenzel, 2016). In contrast to the day-ahead market, the price for primary control power is based on the submitted offer (pay-as-bid auction). As a detailed billing of the provided balancing energy would lead to considerable transaction costs

[7] Unlike conventional power plants, batteries do not have to be in operation generating electricity, but can directly provide positive and negative balancing power, which, in turn, can lead to more flexibility and a lower number of negative prices.

(Swider and Ellersdorfer, 2005), all contracted capacities are compensated only for the capacity provided for the tender period.

Secondary control reserve

All four German transmission system operators jointly estimate the need for negative and positive secondary control power using a probabilistic model. In recent years, the demand for both negative and positive secondary control power has typically varied between 1800 to 2200 MW (50Hertz Transmission et al., 2017).

In contrast to the primary control reserve, suppliers must specify both a capacity as well as an energy price. The capacity price is paid for the provision of capacity in advance. However, the energy price is only paid for the energy requested by the transmission system operator. In theory, the capacity price, therefore, reflects the opportunity costs[8] of a supplier, who can no longer use this capacity for other purposes, such as participating in the day-ahead or intraday market (Singh and Papalexopoulos, 1999). The energy price, on the other hand, is based on marginal costs.

Since July 12, 2018, the secondary control capacity is tendered daily for standardized time slices with a length of four hours. Starting with the lowest capacity price, all bids are accepted until the required amount is reached. The capacities are then sorted in ascending order in a Germany-wide list based on the energy price. In the case secondary control power is requested, capacities are selected based on this list. As of October 15, 2018, a new mixed-price method is applied, also taking into account the weighted energy price (BNetzA, 2018b; Oberlandesgericht Düsseldorf, 2018). The corresponding weighting factor corresponds to the probability with which a control energy type was activated in the last 12 months. This rule is a response to the occurrence of an energy price peak of 77 777 EUR/MWh, on October 17, 2017, and

[8] In reality, the opportunity costs are not always decisive as strategic behavior on the German secondary reserve market can be observed, which leads to a price level that is in some cases far above the competitive level (Ocker and Ehrhart, 2017).

Table 2.4 | Overview of the different types of operating reserves. The three operating reserves differ, for example, in the respective auction dates or lead times. In addition, positive and negative capacities are sometimes auctioned apart from each other. In addition, the remuneration is paid either exclusively for the provision of capacity or also for the energy requested. *Sources:* BNetzA (2011a,b,c, 2017a,b).

	Primary control reserve	Secondary control reserve	Tertiary control reserve
Tender	Weekly	Daily	Daily
Time	Tuesdays 03:00 p.m.	Previous day 08:00 a.m.	Previous day 10:00 a.m.
Complete Activation	≤ 30 s	≤ 5 min	≤ 15 min
Activation time	< 15 min	–	> 15 min
Capacity	positive and negative	positive or negative	positive or negative
Time slices	1	6	6
Time slice length	7 d	4 h	4 h
Minimum lot size	+/– 1 MW	+/– 1 MW	+/– 1 MW
Increment	1 MW	1 MW	1 MW
Bid selection	Capacity price	Capacity price*	Capacity price
Reimbursement	Pay-as-bid (capacity price)	Pay-as-bid (capacity and energy price)	Pay-as-bid (capacity and energy price)

* On October 15, 2018, a new mixed price method was introduced, which takes into account the capacity price and the weighted energy price.

aims to increase competitive pressure in the procurement of secondary control energy and thus to increase the efficiency of the procurement system (BNetzA, 2017b).

Between 2010 and 2015, the costs for providing and utilizing secondary control power have fallen considerably from 505 to 155 million EUR (BNetzA, 2014, 2015, 2016b). In 2014 and 2015, the total amount of negative and positive energy used reached 2.8 and 2.5 TWh respectively.

Tertiary control reserve

The required amount of daily tertiary control power is determined by the transmission system operators. Similar to the secondary control power, the demand for negative and positive control power is determined separately. Between 2010 and 2015, the average volume of the negative and positive tertiary reserve was usually greater than 2000 MW, in some cases almost equal to 3000 MW. Since 2016, the amount has fallen. In 2017, it was typically below 2000 MW for both the negative as well as the positive tertiary reserve. This is partly attributable to the fact that since 2017 trading in the intraday market in Germany is possible up to 30 minutes before delivery for the entire market area or up to 5 minutes before delivery for each individual control area (EPEX SPOT, 2017c). Thereby, deviations can be compensated in advance, and less balancing power is required.

Similar to the secondary control reserve, providers must specify a capacity and an energy price. Bidders have to submit their offers for standardized time slices with a length of four hours. In particular, flexible gas power plants or pumped-storage power plants offer their services in the tertiary control reserve due to their rapid availability and comparatively low opportunity costs. The low opportunity costs are reflected in the capacity price, which often amounts to only a few Euro per MWh, particularly for the positive tertiary control reserve.

In the period from 2010 to 2015, the cost of procuring and providing the tertiary control reserve fluctuated between 49 and 156 million EUR (BNetzA, 2014, 2015, 2016b). In 2014 and 2015, the total usage of positive and negative tertiary control energy amounted up to 361 and 340 GWh and was several times less than the energy required for the secondary control reserve.

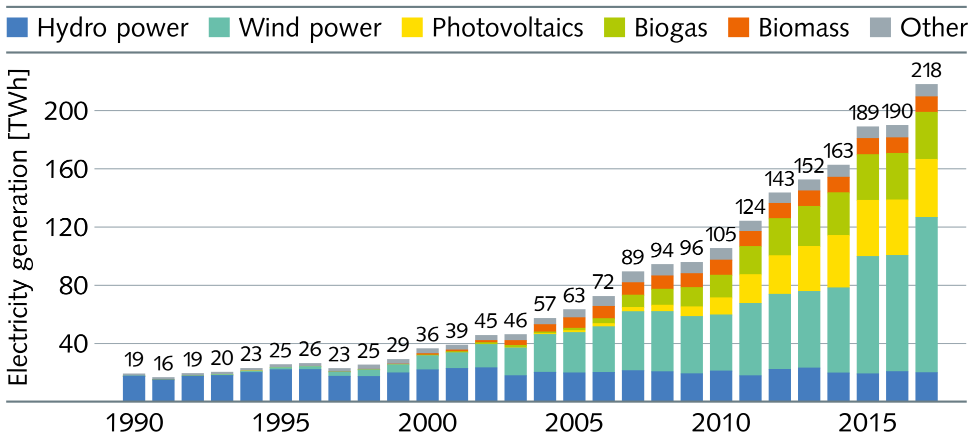

Figure 2.7 | Renewable electricity generation in Germany. Since the introduction of the EEG in 2000, the generation from renewable energies has increased strongly. Biogas, photovoltaics and wind power plants account for the largest share of this development. As the potential of hydropower in Germany has already been widely exploited early on, its generation has remained comparatively constant. *Source:* BMWi (2018c).

2.2 Regulatory and market developments

The German electricity sector has undergone considerable changes in recent years—such as the broad expansion of renewable energies or the European market coupling. Thus, the following sections aim to provide an overview of the most prominent regulatory and market developments in the energy sector as well as to highlight their main consequences, thereby allowing for a more profound understanding of the analyses carried out in this work.

2.2.1 Promotion and expansion of renewable energies

In most European states, various subsidy programs for renewable energies have been implemented to achieve national expansion targets. Germany, one of the pioneering countries in the promotion of renewable energies, introduced the first renewable feed-in law ("Stromeinspeisungsgesetz") already in 1991 (Heinrichs and Michelsen, 2014), which marked the beginning of a tremendous rise of renewable energies (Figure 2.8). The law obliges public utility companies to purchase electricity from renewable energy sources (hydropower, wind power, solar energy, landfill gas, sewage gas or biomass) and to pay a premium calculated as a percentage of the average electricity price to end customers (Bundesregierung, 1990). In this system, the feed-in tariff varied depending on the current electricity tariff, exposing investors to market developments. In times of the monopolistic market, this seemed to be an appropriate solution as prices were both high and comparatively stable. However, after the liberalization of the market in 1998, electricity tariffs decreased and premiums fell. Thus, renewable electricity generators were subject to greater economic pressure (Mitchell et al., 2006). As most renewable technologies could not undercut the electricity generation costs of conventional power plants, technology-specific feed-in tariffs were introduced in 2000 (German Renewable Energy Sources Act, Bundesregierung, 2000). These tariffs guaranteed a fixed purchasing price for the entire electricity produced over a predetermined period, usually 20 years. The payment to the producers is made by the transmission system operators, who then pass the costs on to the final consumers ("Wälzungsmechanismus").

In 2012, the so-called "direct marketing" of electricity from renewable sources was introduced, initially on a voluntary basis (Bundesregierung, 2011b). As a result, it was possible, to market electricity from renewable sources either directly by the owner or via a third party instead of selling it to the responsible transmission grid operator. One aim of direct marketing is to ensure that the electricity generated by renewable energies is demand oriented. Further, it is intended to improve the forecastability, i.e., which renewable energy plant delivers which quantity of electricity at what time, and thereby reduce the use of balancing energy (BMWi, 2017b). Since 1 January 2016, direct marketing has been mandatory for all newly installed renewable energy plants above a size of 100 kW; however, older renewable energy plans can voluntarily choose direct marketing (Bundesregierung, 2016). As the income generated from the sale of the electricity is often not sufficient to refinance an investment, for a period of 20 years, investors receive a so-called floating market premium, which is determined monthly for each technology, such as photovoltaics, wind-onshore or wind-offshore. The value of the market premium corresponds to the difference between a plant-specific reference tariff and the average market value of the specific technology.

In 2017, the subsidy system for renewable energies was changed from feed-in tariffs to recurring auctions (Bundesregierung, 2016). Thus, the remuneration for electricity from renewable energies is no longer fixed but is determined within in pay-as-bid auctions. The Federal Network Agency organizes tenders for onshore wind, offshore wind or photovoltaics. In addition, between 2018 and 2020, joint auctions for onshore wind and solar power plants are carried out. In the first two joint tenders, however, only bids for photovoltaic were accepted, as the bid price for onshore wind was not competitive. Auctions are regarded as a suitable mechanism for the procurement of renewable energy sources; however, whether they meet expectations depends on their design (Kreiss et al., 2017). For example, due to the long-term horizon, there is a risk for the auctioneer that the commissioned bidders may not realize their projects. Financial and physical prequalifications or penalties are discussed as possible countermeasures (Haufe and Ehrhart, 2018).

Limited availability

Many renewable energy sources—photovoltaics, wind or tidal power—are only intermittently available, i.e., unlike conventional capacities, they are not fully dispatchable[9] and cannot produce electrical energy without interruptions (Hirth, 2013). The electricity generated from these intermittent energy sources depends on different local factors such as wind speed, cloud cover or other weather conditions and can vary from day to day, hour to hour, or even minute to minute depending on the installed technology

[9] Even though it is not possible to implement a flexible technical control system for these renewable energy sources, an upper limit for the energy produced can be imposed. In the case of wind turbines, this is achieved through pitch control, which is required, for example, if due to excessive wind speeds the material stress limits of the rotor blades are exceeded.

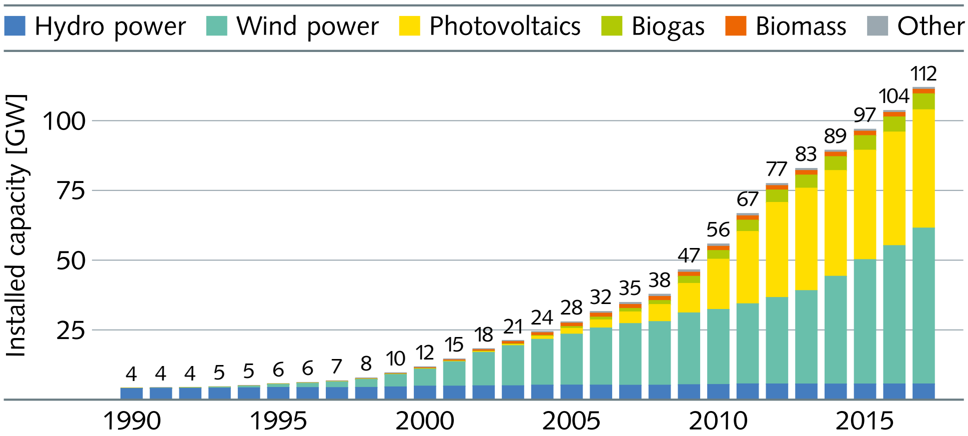

Figure 2.8 | Capacity expansion of renewable energies in Germany. The increase in the installed electrical capacity of renewable energies is evident in the development of wind power and photovoltaics, which in 2017 had a share of 49.9% and 37.9% in renewable capacity. In comparison with photovoltaics, the load factor of wind is significantly higher. Thus, wind power had a similar share of 48.9% in the electricity generation from renewable energies, whereas photovoltaics only accounted for 18.3% (Figure 2.7). *Source:* BMWi (2018c).

and its attributes, e.g., the hub height for wind power stations or the orientation of photovoltaic modules (Joskow, 2011). As the generated electricity from renewable energy sources must be directly consumed, the responsible grid operator has to react using dispatchable capacity to balance supply and demand continuously. Photovoltaic systems, for example, only generate electricity during the hours of daylight, whereby the production usually reaches its daily maximum at noon and yearly maximum during the summer months (Figure 2.9).

In Germany, renewable energies contributed 217.9 TWh to the gross electricity generation in the year 2017, which represents an increase of 144.47 % compared to the year 2007 and is primarily attributable to the expansion of wind, biomass, and photovoltaics (AG Energiebilanzen e. V., 2018). From a European perspective, however, hydropower still has the largest share among renewable energies in 2016, which is explained by the hydro-dominated electricity generation in the Alpine and Scandinavian countries (Eurostat, 2017).

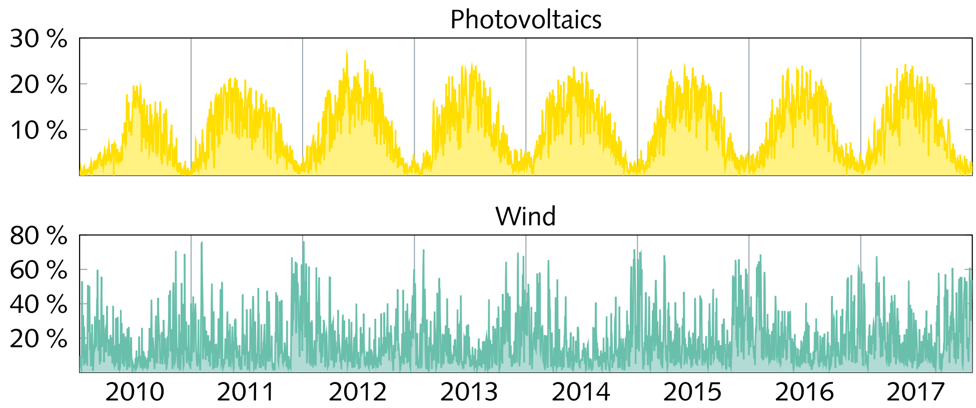

Figure 2.9 | Relative daily photovoltaic and wind feed-in. Over the observed period in the German market, there exist substantial seasonal differences in the relative feed-in[10] from photovoltaic and wind power plants. Whereas photovoltaic modules generate electricity mainly in spring and summer, the most productive months of wind energy lie in autumn and winter. Nevertheless, extreme situations lasting several hours can still occur in which the feed-in of these technologies is either simultaneously extremely low or high. *Source:* EEX (2018a).

2.2.2 European market coupling

The liberalization of the European energy markets is an ongoing process that began in 1996 with the adoption of various legislative packages (European Commission, 1997, 1998), with the aim of creating a fully-integrated internal energy market that would allow barrier-free cross-border trade in electricity and primary energy sources such as oil or natural gas (European Commission, 2010b). The integration of the existing national markets and the resulting increase in competition are intended to reduce electricity costs for consumers (Domanico, 2007; Sadler, 1992). At the same time, security of supply in the participating countries is expected to increase through the further expansion and the better utilization of transmission capacity (Jamasb and Pollitt, 2005).

While market coupling between individual European countries started already early on, e.g., Sweden/Norway (1996) or Belgium/Netherlands/France (2006), the

[10] The relative feed-in is calculated as a quotient of the average daily feed-in and the installed capacity.

connection of the German electricity market to neighboring national markets took considerably longer. On November 9, 2009, for the first time, the German day-ahead market was linked to the Danish market by the Interim Tight Volume Coupling (ITVC)[11]. Shortly afterward, on May 10, 2010, the market coupling with the Nordic regions was established by the already existing Baltic Cable (Böttcher, 2011). Another milestone was the market coupling in Central Western Europe (CWE) at the EPEX SPOT via the implicit auctioning of transmission capacities, which started on November 9, 2010, and covered the following countries: Belgium, France, Germany, Luxembourg and the Netherlands (EPEX SPOT, 2016). Slightly more than three years later, on February 4, 2014, the market coupling was extended to northwestern Europe (NWE) consisting of Belgium, Denmark, Estonia, Finland, France, Germany/Austria, Great Britain, Latvia, Lithuania, Luxembourg, the Netherlands, Norway, Poland, and Sweden.

For cross-border trading, explicit auctions were initially used in which the trade of transmission capacities and electrical energy occurs separately. In order to operate in neighboring markets, market participants had to obtain transmission rights in advance via long-term or short-term auctions. However, explicit auctions have the disadvantage that transmission capacities are not always used efficiently, for example, due to a dominant domestic market participant who under certain circumstances has an incentive to withhold transmission rights or intentionally trade against the price differential (Bunn and Zachmann, 2010).

In order to be able to use the transmission capacities more efficiently, implicit auctions are used nowadays, at which the market participants only place their bids without having to acquire capacities for the transmission of energy in the neighboring countries separately (Oggioni and Smeers, 2013). Subsequently, an algorithm maxi-

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[11] As the name suggests, the *Interim Tight Volume Coupling* was developed as a transitional solution that was later replaced by a more advanced, price-based approach (price coupling). *Tight Volume Coupling* includes all relevant information (market data and rules) so that the quality of the achieved results could be further improved compared to the earlier in place *Loose Volume Coupling*.

mizes the economic welfare in all participating market areas, taking into account the available transmission capacities between the different market areas (Böckers and Heimeshoff, 2014). Within the national market areas, however, it is assumed that there will be no transmission bottlenecks. This approach may result in a situation where the calculated flows in the national power grid are not physically possible. In order to eliminate bottlenecks and ensure the operation of the grid in such cases, network operators must intervene by purchasing additional injection or withdrawal at different nodes of the electricity grid (Oggioni et al., 2012).

As long as sufficient transmission capacities are available between neighboring countries, wholesale prices converge, for example, in 2017, market prices have been identical in Germany and France about 35 % percent of the time. Even if the transmission capacities are not sufficient to achieve a uniform price, the market coupling still affects the prices and the traded volumes in the connected countries.

The accurate assessment of all effects caused by market coupling is a complex problem. Theoretical analyses mostly depend on restrictive assumptions, e.g., complete information, perfect competition, and no uncertainties, which are rarely encountered in practice (Creti et al., 2010). The evaluation under more realistic assumptions, for example, the consideration of existing grids restrictions, requires extensive empirical models in most cases. In an analysis for the year 2012, Newbery et al. (2016) estimate a welfare gain of 3.80 billion EUR from coupling all electricity markets in the EU. This would result from the coupling of the day-ahead market (1.01 billion EUR) as well as the coupling of the intraday market (37 million EUR), from shared balancing (1.34 billion EUR), from the minimization of unscheduled flows (1.36 billion EUR) and from less curtailed renewable energy (130 million EUR).

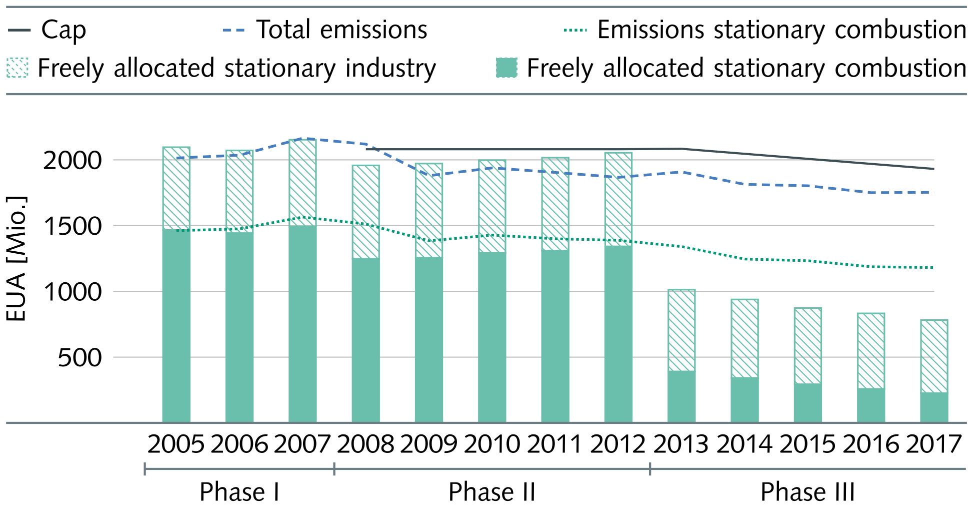

Figure 2.10 | Development of the free allocation of emission allowances and emissions covered by the EU-ETS. In the first two trading periods, participating companies were able to cover their demand almost entirely by freely allocated allowances, but, in the third period, free allocation was substantially reduced. In this phase, electricity generators no longer receive free allowances, except in eight member states where free allowances can be granted for the modernization of power plants or investments in clean technologies. *Sources:* European Commission (2007, 2010a,b); EEA (2018).

2.2.3 European Union Emission Trading Scheme

The European Union Emissions Trading System (EU-ETS) is the first international and one of the world's largest trading system for emission allowances. It is a central instrument of European climate policy facilitating an efficient reduction of European greenhouse gas emissions (Eugenia Sanin et al., 2015). In 2003, the Directive 2003/87/EC established the legal basis for the EU-ETS, which came into force on January 01, 2005 (European Commission, 2003b). The EU-ETS represents a cap-and-trade system, in which an upper limit of greenhouse gas emissions (*Cap*) is defined that cannot be exceeded. Each installation covered by the scheme needs an equivalent amount of allowances for its emissions; otherwise, a penalty is imposed.

Allowances can either be freely allocated (*grandfathering*) or auctioned by a regulatory body (Cramton and Kerr, 2002). Once allowances are in circulation, trade

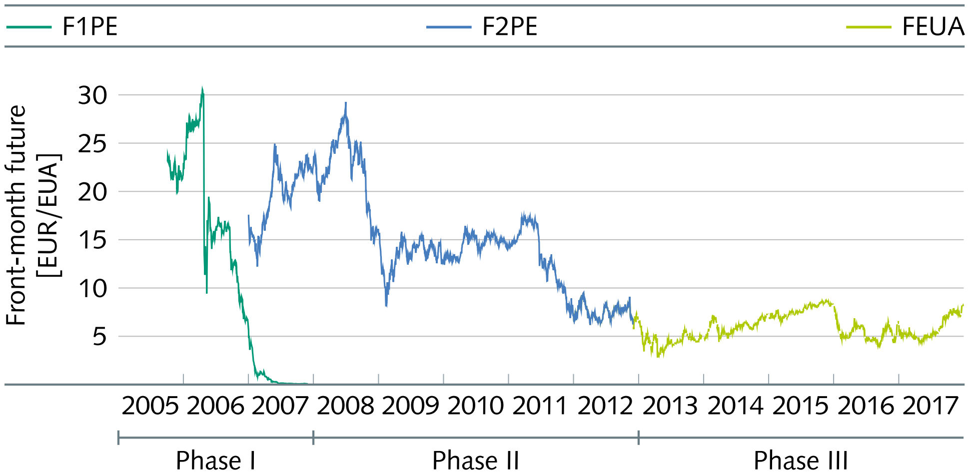

Figure 2.11 | Historical prices of EUA futures. The price development of emission allowances shows significant volatility, especially in the first phase. The oversupply of allowances and the ban on banking between the first and second phase resulted in a sharp price drop from 30 to 0 EUR/EUA within only 12 months (Hintermann, 2010). In the third phase, the price has been at a comparatively low level of less than 10 EUR/EUA, prompting the European Commission to intervene in the market. First, the auctioning of 900 million allowances was postponed by several years (back-loading). Subsequently, these allowances were transferred to a market stability reserve, which was implemented to address the surplus and improve the resilience of the system to extreme shocks affecting market supply. *Source:* EEX (2018a).

between the individual market players is opened. In this manner, the marginal reduction costs of all participating entities are leveled, and an economically efficient solution can be achieved (Montgomery, 1972). Profit-maximizing companies reduce their emissions as long as it is less expensive than acquiring allowances on the market. At the same time, companies with low-cost options for emission reductions have an incentive to sell unneeded allowances to market participants with higher savings costs. The resulting market price is equal to the costs of reducing the emissions to one unit below the cap, often referred to as the market's marginal abatement cost (Hintermann et al., 2016).

The EU-ETS covers the energy sector and the energy-intensive industry, which in total includes over 12 000 installations within the European Union that account for about 45 % of total greenhouse gas emissions of all participating countries (European Commission, 2017a). To date, trade in the EU-ETS can be divided into three periods. The first trading period lasted from 2005 to 2007 and served as a trial period. The second trading period has already benefited from initial experiences and ran from 2008 to 2012. The third trading period began in January 2013 and will end in December 2020.

In the first and second period, the majority of the allowances were freely allocated (Figure 2.10). However, as the allowances possess a value, the electricity price increased leading to so-called "windfall profits" in the energy sector as for the affected companies no costs incurred[12].

The electricity sector plays an essential role in the reduction of emissions within the EU-ETS. In the short term, electricity producers have the opportunity to reduce their emissions without additional measures through a fuel switch, usually from hard coal to natural gas (Hintermann et al., 2016). The EU-ETS also has a central influence on investments in the electricity sector. A severe difficulty for investors is to estimate the future development of the price of emission allowances, whose course partly shows highly volatile developments (Figure 2.11). This and the uncertainty about the future conditions of the EU-ETS have undermined the potential of the EU-ETS to stimulate substantial investments required for the decarbonization of the electricity sector (Laing et al., 2014). Therefore, targeted measures—in particular the promotion of renewable energies—are still necessary.

Although, in theory, the market price for allowances equals the marginal reduction costs, in practice, the formation of prices is much more complex. An essential factor for the low price in the second phase seemed to be the world economic crisis, which temporarily reduced the production of many companies and, in turn, led to a surplus of allowances (Bel and Joseph, 2015). The cumulative surplus was estimated to be approximately 1.80 billion EUA in 2012, which approximately corresponds to emissions

[12] For a detailed discussion see, for example, Sijm et al. (2006) and Laing et al. (2014).

of one whole year (Ellerman et al., 2014). However, it is still debated which factors drive the price formation. For example, Koch et al. (2014) argue that abatement-related fundamental factors only explain 10 % of the changes of the allowance price.

2.2.4 Climate contribution and climate reserve

Since the early 1990s, CO_2 emissions in Germany have fallen significantly, but recently this development has stagnated. One reason for this is the low price for CO_2 emission allowances, which has been in the range of 5 to 10 EUR/EUA since 2011 (Figure 2.11). This offers only a limited incentive to implement CO_2 abatement measures. As almost half of the national CO_2 emissions stem from the energy sector (UBA, 2017), the developments in this sector, especially the low coal price, also have a significant influence (Figure 2.12). As a result, the marginal costs of emission-intensive coal-fired power plants are comparatively low, and low-emission gas-fired power plants are rarely operated. If the underlying conditions remain unchanged, there is a risk that the climate target for 2020 set by the German government of achieving a reduction of carbon dioxide (CO_2) emissions by 40 % compared to 1990 might not be achieved (BMWi, 2015a). To prevent this, various countermeasures have been proposed to reduce emissions from all sectors by additional 59 million t CO_2 compared to 2014.

Original climate contribution (March 2015)

The national policy instrument proposed under the term "climate contribution" aimed at reducing carbon emissions by 22 million t CO_2 and at the same time causing only low transaction costs and a slight increase in the wholesale electricity price. For this purpose, all conventional power plants—except for units younger than 20 years[13]—would have to acquire additional allowances for emissions that exceeded an age-dependent and performance-specific amount of allowances. Subsequently, these

[13] The age referred to the year of commissioning, provided that no major retrofitting measures, such as boiler replacement, had been carried out. Otherwise, the age was determined depending on the date of the measures taken.

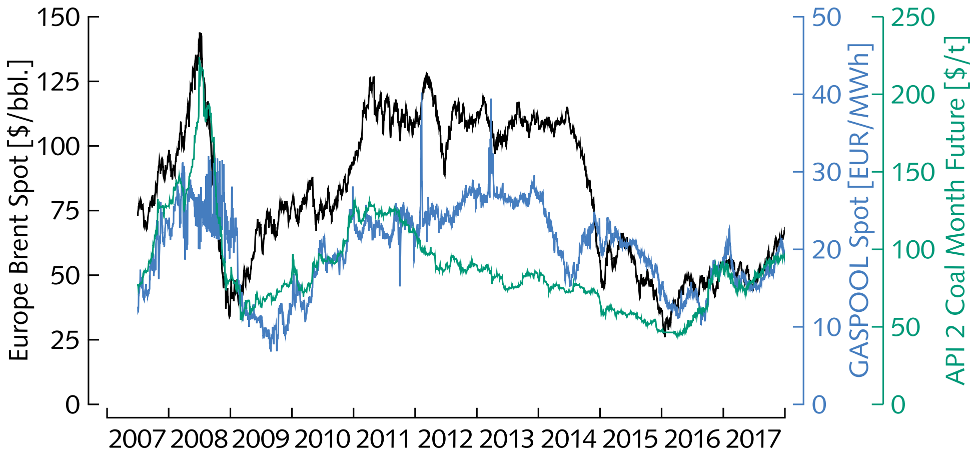

Figure 2.12 | Development of natural gas, hard coal, and oil prices. Fuel prices can be subject to extreme fluctuations within short periods of time. For example, in 2008, the Brent crude oil price first rose strongly and then dropped from 144 to 34 USD/bbl. Similarly, the price of the monthly API-2-Coal Future fell from 224 to 74 USD/t. In 2011, the coal price started to decline, whereas the gas and oil prices began to fall in 2014—in the case of oil even sharply—a trend that continued until 2016. Thereafter, the price of natural gas and coal recovered and, at the end of 2017, reached 20 EUR/MWh and 100 USD/t, while at the same time the oil price is still at a comparatively low level of 50 USD/bbl. *Sources:* EEX (2018a); EIA (2016).

allowances would be canceled, i.e., finally withdrawn from the EU-ETS (BMWi, 2015a). The number of allowances to be submitted should depend on the current market price in order to ensure that the reduction target is achieved even in the scenario of a low allowance price. The value of the required allowances should be in the range of 18 to 20 EUR CO_2/t in 2020, with the plan to steadily increase the value by 1 EUR CO_2/t per year starting in 2017 (Öko-Institut and Prognos, 2015).

Although the first version of the climate contribution was predominantly positively evaluated by experts, public utilities as well as political parties, criticism was expressed by the Mining, Chemical, and Energy Industries Union (IG BCE) and by energy suppliers, which operate large capacities of lignite-fired power plants (DIW, 2015). Both of the latter warned of a possible structural change, which would be accompanied by several decommissions of lignite-fired power plants and closures of opencast lignite

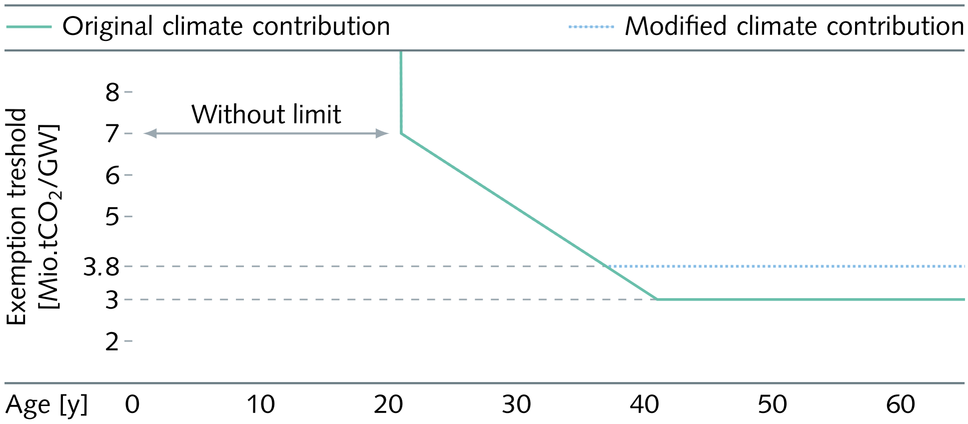

Figure 2.13 | Exemption thresholds for the climate contribution. Power plants received different exemption thresholds, depending on the number of years since commissioning. Newer power plants (age ≤ 20 years) were excluded from the climate contribution. From the age of 20 years, the exemption threshold equaled 7 million t CO_2/GW and decreased linearly with each subsequent year until it reached a base amount of 3 million t CO_2/GW in the initial proposal. In the modified proposal, the base amount was raised to 3.80 million t CO_2/GW, in particular, to improve the profitability of older lignite-fired power plants and to avoid economically induced decommissions. *Source:* BMWi (2015d).

mines (Frontier Economics, 2015). As a result, the Federal Ministry for Economic Affairs and Energy (BMWi) saw a need for action and shortly afterward drafted a revised version, in which the points of criticism were addressed.

Modified climate contribution (May 2015)

Whereas in the original version of the climate contribution aimed at an additional reduction of 22 million t CO_2, the modified version foresaw only a reduction of 16 million t CO_2 in order not to unduly impair the profitability of the national power plants. The difference of 6 million t CO_2 was supposed to be compensated by further measures, i.e., an increase in combined heat and power (CHP) funding, pilot projects in the transport sector for electric trucks, and increased efforts in the rail sector (BMWi, 2015d). The adjustments took place on several levels. On the one hand, the

Table 2.5 | Indexed climate contribution. In the modified version of the climate contribution, the value of the additionally required allowances depended on the prices of the "Phelix Base Year Futures" and the EUA futures of the next year or, if necessary, the year after next. *Source:* BMWi (2015d).

Phelix Base Year Future [EUR/MWh]	EUA Future [EUR/EUA] 7.50	10.00	12.50	15.00	17.50	20.00
28	3†	0*	0*	0*	0*	0*
30	6†	0*	0*	0*	0*	0*
32	14‡	5†	0*	0*	0*	0*
34	15‡	8†	4†	0*	0*	0*
36	16‡	14‡	7†	0†	0*	0*
38	18‡	15‡	12‡	6†	0†	0*
40	19‡	17‡	14‡	11‡	5†	0†
42	20‡	18‡	15‡	13‡	10‡	0†
44	20‡	19‡	16‡	14‡	11‡	6†

* According to the BMWi, the high allowance price already led to coal-to-gas fuel switching, but the comparatively low electricity price only caused isolated decommissions. Therefore, the emission reduction target of 16 million t CO_2 could be reached without additional measures.

† To avoid additional decommissions due to low contribution margins, the value of the climate contribution was adjusted downwards, at the risk that the reduction target may not be fully achieved.

‡ In these cases, which were considered likely by the BMWi, the climate contribution was required in order to achieve the targeted reduction, as the low allowance price by itself would not achieve any or only marginal emission reductions. Nevertheless, the power plant operators could generate sufficient contribution margins.

Table 2.6 | Power plant units for backup purposes. The listed lignite-fired power plant units have already been or will soon be mothballed and onwards will be used for backup purposes only. The units remain in standby mode for a maximum of four years and will then be permanently decommissioned. *Sources:* BMWi (2015c); BNetzA (2016a).

Admission date	Power plant	Unit	Net capacity [MW]	Initial operation
10/01/2016	Buschhaus	D	352	1985
10/01/2017	Frimmersdorf	P	284	1966
10/01/2017	Frimmersdorf	Q	278	1970
10/01/2018	Niederaußem	E	295	1970
10/01/2018	Niederaußem	F	299	1971
10/01/2018	Jänschwalde	F	465	1989
10/01/2019	Neurath	C	292	1973
10/01/2019	Jänschwalde	E	465	1987

base amount, i.e., the amount of carbon each power plant was permitted to emit without further restrictions, should be increased (Figure 2.13). In addition, the value of the additional allowances—which operators had to acquire through the EU-ETS—should be linked to the electricity and allowance prices for a dynamic adaptation to market developments.

Standby mode for backup purposes of lignite-fired plants

Instead of the climate contribution, Frontier Economics (2015) proposed to gradually implement a "reserve for security of supply and climate protection" consisting of coal and lignite power plants to reduce the emissions by a total of 11 to 16 million t CO_2 by 2019. However, this measure was considered to be inefficient and costly by the BMWi. As a result, a joint compromise proposal was drawn up, which, among other things, provided for the exclusion of 2.7 GW of lignite-fired power plants from regular market operation, for which the operators were granted a financial compensation (Oei et al., 2015). Thereby, emissions are expected to be reduced by 11 to 12.5 million t CO_2, at the same time the total reduction target for the electricity sector was lowered and is now set to 14 million t CO_2 (BMWi, 2015a).

The selected lignite-fired power plants, which were determined in a non-public process, are mainly older power plants (Table 2.6) with an efficiency of less than 40 % (Open Power System Data, 2017). These units are located in different lignite mining region (Lusatian district in Brandenburg, Rhenish district in North Rhine-Westphalia, and Helmstedt district in Lower Saxony) in order to avoid possible regional structural breaks. However, this line of argumentation was subject to criticism as the likelihood of these structural breaks was classified as low by the DIW (2015). The annual costs for the standby mode of the lignite-fired plants amount to around 230 Mio. EUR, which corresponds to an increase in network charges of approximately 0.05 Cent/kWh (BMWi, 2016b). However, as the lignite-fired power plants selected for the standby mode are located north of the bottlenecks in the transmission grids, redispatch costs should decrease.

To use the power plants, first a lead time of 240 hours is required to switch to operational readiness and then further 11 or 13 hours are needed to reach minimum partial load and full load respectively (BMWi, 2015c). As a result, the power plants in standby mode are unable to react to unexpected events at short notice.

2.2.5 Capacity reserve

With the decline in wholesale prices and the corresponding decreasing margins, power producers operating on the German market are exposed to growing economic pressure. As a result, an unusually high number of capacities have already been decommissioned, and closure notifications for many other power plants have been submitted (Figure 2.14). Although the decommissioning of power plants is an economic necessity from the viewpoint of supply companies, security of supply is dependent on sufficient dispatchable capacities. In 2014, the surplus capacity[14] in Germany was estimated at around 8 GW, whereas a value of 5 GW is reported for 2015 (ENTSO-E, 2014). According to a more recent analysis, generating capacities will be able to cover the peak load at all times in the near future in Germany, but with the expected decommissioning of conventional power plants, this could change starting in 2020 (ENTSO-E, 2015). The developments described together with the slow expansion of the transmission network have triggered a debate on capacity remuneration mechanisms in Germany, in particular, the implementation of a strategic reserve. Capacity remuneration mechanisms are economically advantageous if they help to overcome the market imperfections[15] of the electricity market.

The central concept of a strategic reserve is to maintain a certain level of generation capacity, which no longer participates in regular market activities. In shortage situations, this capacity can be deployed by the regulator to ensure that the demand is always satisfied. Whereas a strategic reserve has the advantage of being fairly straightforward to implement and, if necessary, to dissolve, it also entails serious disadvantages (Cramton et al., 2013). Firstly, the power plants included in the reserve are not allowed to participate in other market activities, which leads to the inefficient use of the existing capacities. Secondly, it is challenging to design the strategic reserve without distorting the market, i.e., ensure that in case the reserve is dispatched, the resulting market price corresponds to the value of lost load (VoLL)[16]. If the value at which the reserve is offered in the market is not sufficiently high, market prices will be below those of an efficient spot market, and new investments may be suppressed.

[14] The surplus capacity is defined as the difference between the reliable available capacity and the load.

[15] Among the various market imperfections, the central problem of the electricity market is to generate prices that reflect the opportunity costs of consumers in times when all capacities are already fully utilized (Cramton et al., 2013).

[16] The value of lost load describes the average willingness of customers to pay for the reliability of their electricity supply. The individual willingness to pay can vary between close to zero and tens of thousands of Euros per MWh, whereby extremely high values are typical for critical infrastructures such as hospitals (Hogan, 2017).

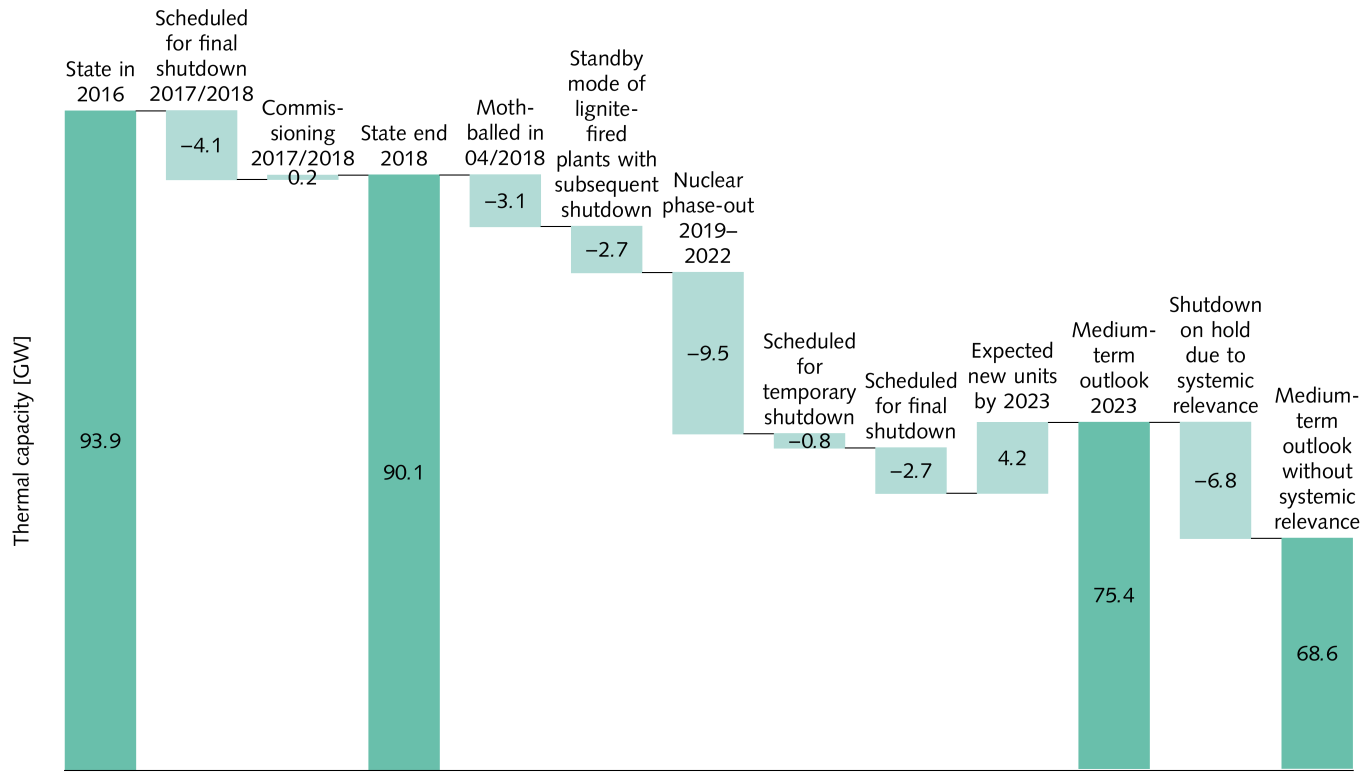

Figure 2.14 | Expected development of thermal capacity in Germany until 2023. The German Association of the Energy and Water Industries (BDEW) expects thermal capacities to decrease by 3.8 GW by the end of 2018 and by 18.5 GW by 2023 taking into account all power plants, which are planned or under construction and possess a high probability of completion. A major driver of this decline is the phase-out of nuclear power. However, the future construction and closure of power plants are subject to considerable uncertainties and depends on the decisions of political and economic stakeholders. *Source:* BDEW (2018).

Furthermore, even if it was possible to determine the VoLL precisely[17], its value only corresponds to the average willingness to pay. Consumers whose individual VoLL is below the average would be forced to spend more than they are willing to.

When designing the strategic reserve, Germany was able to draw on the experience of other European countries such as Sweden, Denmark, Poland or Belgium (BMWi, 2014, 2015b,c; Consentec, 2012). The final concept defined by the German Energy Act stipulates that both old and new plants may participate in the procurement process. In contrast to the grid reserve, all capacities are procured within the framework of a central and open auction. No capacities that are once part of the reserve may participate in other markets, not even against the payment of a premium. Although initially the reserve was supposed to be offered in the day-ahead market (BDEW et al., 2013), the now valid concept provides that the reserve is only activated if a physical deficit occurs that cannot be compensated by other measures (Figure 2.15). After initial concerns of the European Commission about compliance with EU State aid rules, the draft of the capacity reserve has been approved and, starting in 2019, 2 GW are to be contracted for each 2-year period until 2025 (European Commission, 2018c).

[17] Currently, the VoLL cannot be determined precisely, but only be estimated by aggregating more or less representative data of the different types of consumers (Coll-Mayor et al., 2012). This, however, may change due to the rollout of smart meters and the resulting increasing availability of real measured data.

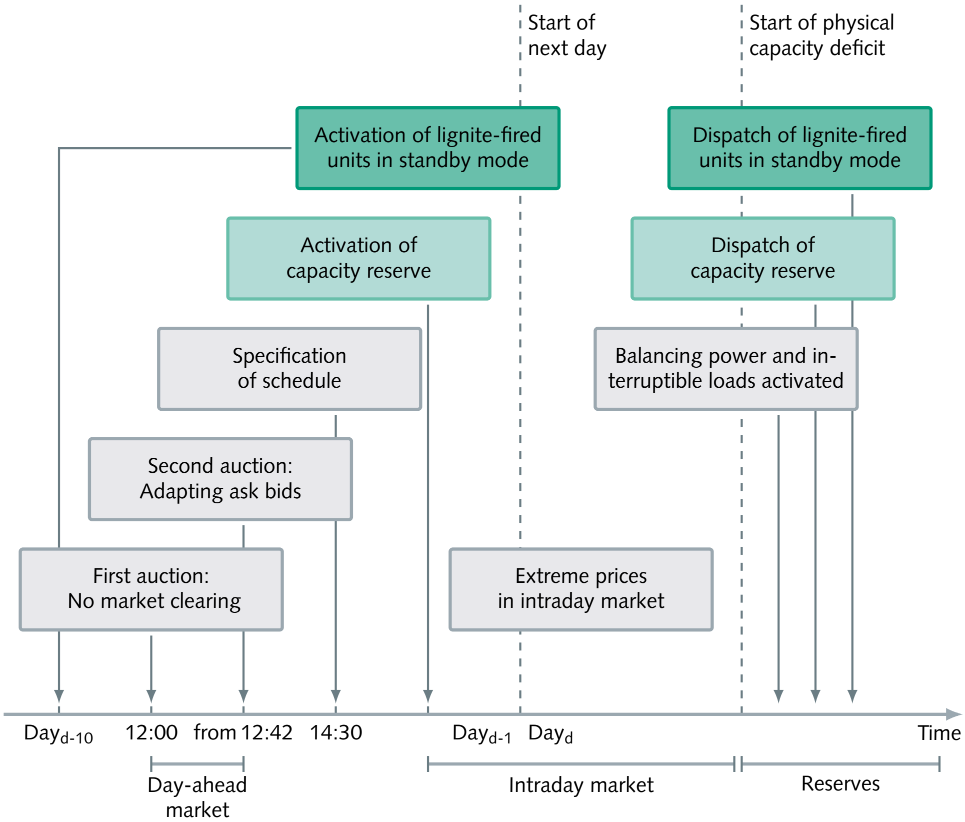

Figure 2.15 | Operation of the German capacity reserve. The capacity reserve is used in the event of a capacity deficit that cannot be compensated even though all existing measures have already been applied. If in the first auction of the day-ahead market, the amount of electricity is insufficient to meet the demand, a second auction may be held in which the market participants adapt their buy and sell bids. If the market cannot be cleared in this auction as well, various power plants in the capacity reserve will be put on standby, i.e., the units will be started up, ramped up to minimum load so that they can be switched to full load operation at short notice by the transmission system operator. During the activation phase, in order not to interfere with the functioning of the intraday market, transmission system operators must request active units to ramp down by the amount generated by the units in the capacity reserve. If on the next day, despite high prices in the intraday market, sufficient capacities are still not available, the different operating reserves and interruptible loads are activated. If the available positive control power and interruptible loads have largely been exhausted, but the capacity deficit is still not eliminated, the units of the capacity reserve, which are already running at minimum load, are dispatched at full capacity. *Source:* BMWi (2015b, 2018b); European Commission (2017b).

Chapter 3
Techno-economic models for electricity systems

According to Hamming (1962), the purpose of computational calculations is not to generate numbers, but to gain insights. This idea played an integral role in the development of the first energy system models following the oil price crisis in the 1970s (Huntington et al., 1982), when policymakers and business leaders sought to gain a better understanding of the long-term impact of energy-related decisions (Pfenninger et al., 2014). In the process of time, the demand for decision support has strongly grown, and with it, the demands on the models have risen as well (Ventosa et al., 2005), which, for example, is reflected in the growing number of energy system models (Nakata et al., 2011). In this context, an increasing number of specialized models have been developed that deal with only one specific aspect of energy: electricity (Bazmi and Zahedi, 2011). These dedicated models can include both short-term aspects, e.g., the daily power plant dispatch, and long-term decisions, e.g., power plant investments with a time horizon of more than 20 years.

This chapter first addresses the requirements for electricity system models. This is followed by a description of the various possible model classifications, the fundamental properties of the most common model types as well as their specific strengths and deficits. Subsequently, the suitability of the model types for the research questions of this work is examined. Finally, further challenges in the field of electricity system modeling are addressed.

3.1 Model requirements

This section outlines the requirements for a model that reflects the characteristics of the European electricity sector. On the one hand, the essential components of the sector, such as the various markets or actors, are described and, on the other hand, technical model characteristics, e.g., the temporal resolution, are addressed.

In the past, state-regulated monopoly operators were present in the electricity sector, which meant that the representation of different market participants could be neglected. However, as current developments are primarily influenced by the decisions and the interactions of individual market participants, the following real-world aspects should be taken into account when modeling the electricity sector: asymmetric information, imperfect competition, strategic behavior and collective learning (Tesfatsion, 2002). These aspects, however, pose significant challenges for most of the established approaches.

Although electricity is also traded over-the-counter between market players, the central day-ahead auction at the EPEX SPOT is considered one of the most prominent trading venues whose price signals are of great significance for the entire electricity sector. Due to the manifold ways of marketing energy or power, e.g., via balancing power markets, interdependencies between different market segments exist. As a result, the capacity that has already been sold to provide positive balancing power can no longer be offered on the day-ahead market. In addition, the provision of negative balancing services by power plants must be taken into account when submitting bids for the day-ahead market, which in turn can lead to negative prices (see Section 2.1.3). Thus, to be able to model the price formation in the day-ahead market appropriately, it is of high relevance to take these circumstances into account.

Given that most European countries are tightly connected to their neighboring states through the European continental network, an isolated national approach does not seem to be expedient. Instead, neighboring market areas must also be integrated into models with a national focus. For instance, the electricity flows into and out of

Germany or Switzerland amount to more than 100 TWh and 67 TWh per year, which corresponds to 19 % and 107 % of the gross national consumption (AG Energiebilanzen e. V., 2018; BFE, 2018). This is related to the fact, that although the different day-ahead markets in Europe are mostly restricted to national territories, the vast majority of them—representing about 85 % of European power consumption (EPEX SPOT, 2018b)—is linked via a sophisticated market-coupling algorithm at the EPEX SPOT (see Section 2.2.2). Thus, market results are influenced by bids from abroad.

A characteristic feature of electricity is that it can be stored on a large scale currently almost exclusively by pumped storage power plants, whose potential, however, is quite limited. At the same time, the demand for electricity is comparatively inelastic (Lee and Lee, 2010). Hence, the electricity generation must adapt to the demand. Therefore, models that exclude essential technical restrictions, such as the start-up times of power plants, are only partially suitable for modeling electricity markets (Ventosa et al., 2005).

The changing framework conditions in the electricity sector poses significant challenges for decision-makers. This applies in particular to decisions on investments, whose value is strongly influenced by the uncertain development of various long-term factors. For this reason, it is necessary to consider the uncertainties mentioned in the previous chapter, e.g., prices of fossil fuels and emission certificates, technological processes, the feed-in of volatile renewable energies, the behavior of market players as well as the development of political and regulatory framework conditions (Möst and Keles, 2010).

During the liberalization of the electricity sector, the regulatory and political framework has changed profoundly, and it is expected that in the future the electricity sector itself will undergo a fundamental process of change. This process is heavily influenced by Germany's climate policy goals and the associated growing share of renewable energies. Furthermore, the introduction of new interdepending markets such as the European emissions trading scheme or the strategic reserve (see Section 2.2.5) shows that a model should be flexible and expandable in order to simulate current and possibly new future market elements.

3.2 Model classification

A multitude of different models has already been developed to analyze the electricity sector, which, for example, can be seen in the numerous publications that reflect the state of research in a selected sub-area, e.g., modeling of decentralized electricity systems (see Table 3.1). In view of this situation, it is appropriate to adopt a classification to gain an overview of the numerous models and at the same time to be able to assess their various properties.

A substantial complication is however that the literature does not contain a uniform, but manifold classifications. According to Ventosa et al. (2005), energy system models can at the top level be divided into the following classes: Optimization models, equilibrium models, and simulation models. Sensfuß (2007) adopts a similar classification for energy system models, however, in addition, the different perspectives in modeling, either “bottom-up” or “top-down,” are included. Top-down models take a systemic, macroeconomic perspective; in contrast, bottom-up models are based on a microeconomic foundation (Böhringer, 1998). Top-down models are able to replicate, e.g., economic reactions to political shocks, but usually possess a very simplified representation of the energy system and disregard sectoral or technological details (Böhringer and Rutherford, 2008). Bottom-up models, on the contrary, integrate the specific characteristics of the electricity sector, such as the multitude of different generation technologies and energy carriers. However, the macroeconomic effects of energy policy decisions are mostly neglected.

If the focus is on a particular aspect of the electricity sector, such as the price of electricity, a different classification is preferable. Here, Möst and Keles (2010) distinguish between econometric, financial, game-theoretic and fundamental models (see Figure 3.2). Nonetheless, in some cases, it is difficult or even impossible to assign

Table 3.1 | Reviews of electricity market/system models. In the literature, there exists a multitude of different approaches. However, many of the models considered in the following surveys share strong similarities by being bottom-up models and employing either optimization methods or relying on agent-based simulation.

Publication	Topic	Scope
Bazmi and Zahedi (2011)	Modeling, optimization, and simulation of the energy and electricity sector	55 publications
Connolly et al. (2010)	Integration of renewable energies into electricity systems	37 models
Foley et al. (2010)	Models of electricity systems	7 proprietary models
Guerci et al. (2010)	Agent-based models of electricity markets	49 models
Möst and Keles (2010)	Stochastic modeling of electricity markets	20 models
Ringler et al. (2016)	Agent-based models of decentralized markets and smart grids	18 models
Sensfuß et al. (2007)	Agent-based models of electricity markets	14 models
Ventosa et al. (2005)	Modeling of electricity markets	36 models
Weidlich and Veit (2008)	Agent-based models of electricity markets	26 models

a model to a single category, especially with hybrid models that attempt to combine the advantages of different approaches in a single model (Böhringer, 1998).

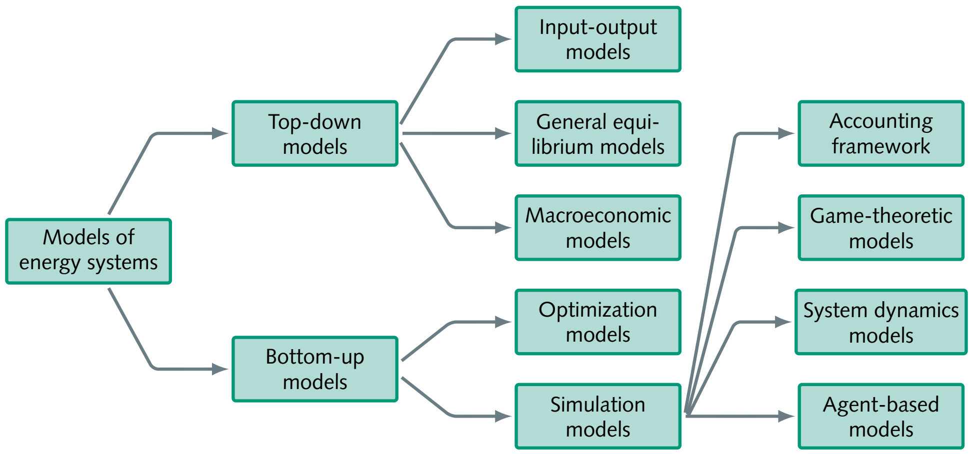

Figure 3.1 | Overview of different model types for energy systems. Sensfuß (2007) first introduces a classification into top-down and bottom-up models and, compared to Ventosa et al. (2005), takes into account additional modeling approaches (macroeconomic and input-output models), which are mainly applied to energy systems instead of electricity markets.

3.3 Model approaches

The subsequent sections describe the most common model classes based on the classifications described at the beginning: optimization models, agent-based models, equilibrium (game-theoretical) models, system dynamics models, financial (quantitative, stochastic), and statistical (econometric) approaches.

In addition, it is noticeable that a large part of the most recently developed models (Bazmi and Zahedi, 2011; Connolly et al., 2010; Ringler et al., 2016; Weidlich and Veit, 2008), falls into the category of optimization or agent-based simulation models. This seems to be related to the fact that both types of models as bottom-up models combine the ability to represent energy systems in great detail, which is of immense importance for a broad range of energy economic research questions. In view of the relevance of these approaches, both are examined and compared in more detail (see Table 3.2).

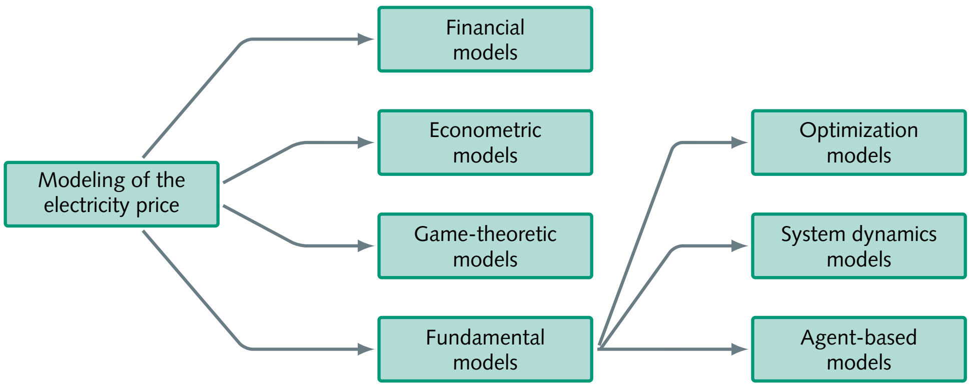

Figure 3.2 | Overview of different types for the modeling of electricity prices. Möst and Keles (2010) make a further segmentation by also considering econometric and financial mathematical models. However, contrary to Sensfuß (2007), game-theoretical models are considered as a separate category and not as a sub-category among the fundamental models.

3.3.1 Optimization models

Optimization models of an electricity system usually aim to minimize costs and at the same time satisfy a given demand at all times. One the one hand, the short-term unit commitment, in which technical restrictions such as the load gradients of thermal power plants or the flow rates at pumped-storage power plants, can be taken into account. On the other hand, long-term investments in renewable energies or the expansion of interconnector capacities can be included (Fürsch et al., 2013). For long-term decisions, either a time-step (also myopic-dynamic) or perfect-foresight approach is applied (see Figure 3.3). Whereas in the former, successive optimizations over sequential time periods are carried out, in the latter, a single optimization is performed over the entire period under consideration (Keppo and Strubegger, 2010).

As different actors cannot be included in optimization models, they take the perspective of a central planner or an individual company and are analogously referred to as "single-firm optimization models" (Ventosa et al., 2005). As a general principle, it is usually assumed that this actor possesses perfect information, for example, with

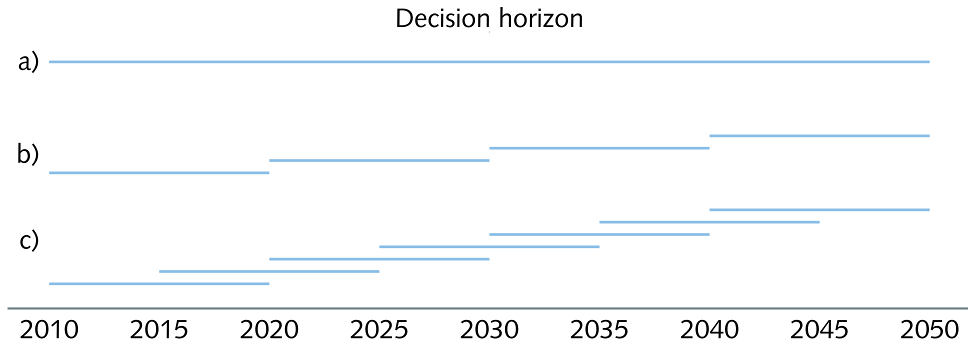

Figure 3.3 | Decisions in optimization models assuming limited or perfect foresight. In *case a)* a perfect-foresight approach is adopted; therefore, the decision horizon corresponds to the entire period regarded. Right from the beginning, all information with relevance for the decision-making process is available. For this reason, there is no need to make any subsequent decision or even revise a previous decision. In *case b)*, a time-step approach is used, and first, a decision is made that only affects the first part of the observation period. In 2020, a subsequent decision will be taken for the remainder of the observation period. However, this will not affect the outcome of the irreversible decision already taken before. In *case c)*, decision-making processes are probably implemented most realistic by allowing for partially reversible decisions. If after 5 years new information becomes available, the last decision taken can be altered. In case of a revised decision, due to the 10-year horizon, however, only the last five years are affected. *Source:* Keppo and Strubegger (2010).

regard to all the technical equipment and investment options as well as the future demand for electricity.

Despite the immense computing power available today, often simplifications have to be made in order to calculate optimal results when the specific characteristics of different generation technologies are considered. This includes, for example, the aggregated representation of generation capacities at the national level (e.g., Traber and Kemfert, 2011) or a limited temporal resolution, where representative days, e.g., 2 days for each season, and representative years, e.g., 5 or 10-year intervals, are selected (cf. Blesl et al., 2007). However, these simplifications can lead to results deviating from the optimum. As the extent of the deviation usually depends on the input data in a non-linear manner, it is extremely complex to estimate the exact effect, which makes the interpretation of the analysis performed quite troublesome (Frew and Jacobson, 2016; Poncelet et al., 2016). For example, Haydt et al. (2011) show by comparing models with a low or high temporal resolution, e.g., 288 or 8760 time periods per year, that significant divergence can occur, especially with regard to the share of fluctuating renewable energies and the associated CO_2-emissions of the electricity system.

Since the beginning of energy system modeling, optimization models have played a prominent role, and today are probably the most widespread model type. In the field of optimizing energy system models, prominent examples include, among others, MARKAL/TIMES, PRIMES, EnergyPLAN, IKARUS and PERSEUS (Connolly et al., 2010). Among these, MARKAL/TIMES is probably the best-known model family, whereby the former stands for "Market Allocation" and the latter for "The Integrated MARKAL/EFOM System" (Loulou, 2008; Loulou and Labriet, 2008). Herewith it already becomes clear that TIMES is based on MARKAL and can be regarded as its evolutionary advancement. Within TIMES, some of the original criticisms of the economically oriented MARKAL could be addressed by integrating the technical model EFOM (Energy Flow Optimization Model) that represents a network of different locations for energy conversion, energy-intensive products, and primary energy carriers (Remme et al., 2002).

MARKAL/TIMES was developed by a consortium of researchers from the IEA member states and is aimed at investigating future energy developments based on contrasting scenarios. Alone in 2015, TIMES was used in 70 countries and at 177 institutions (Chiodi et al., 2015).

3.3.2 Agent-based models

Over the past two decades, coupled with the broad availability of high-performance computing power, agent-based simulation, has experienced extensive growth and is also established and widely deployed in the energy sector (cf. Guerci et al., 2010; Sensfuß et al., 2007; Weidlich and Veit, 2008). Another aspect fostering this development is the fact that the consideration of different market participants has become increasingly significant. This is a direct result of the liberalization of electricity markets, in the course of which national markets have evolved from integrated monopolies to liberalized markets with numerous market participants. Furthermore, the possibilities of agent-based models are numerous and multifaceted. Axelrod (1997) even calls the agent-based simulation “a third way of doing science” that complements the conventional inductive and deductive approaches.

In agent-based modeling, economic systems are considered complex dynamic environments, in which agents follow their custom strategies to pursue partly contradictory targets and are able to adapt their behavior to the current environment. In this context, the term “agents” is defined comparatively broadly and includes among others individuals (consumers, employees), economic entities (companies, regulatory authorities), institutions (regulatory systems) as well as physical entities (transmission networks, power plants) (Tesfatsion, 2006).

In general, agent-based models consist of a system of computational structures and rules to simulate the actions and interactions of predefined agents, with the aim of assessing their impact on the system as a whole. For this purpose, in a first step, a model is created, which includes an initial population of agents, and the initial state of the system is specified by defining the attributes of the agents—e.g., learning behavior, knowledge about the environment.[1] Subsequently, the model is executed without any further adjustments, i.e., all observed events must result from the interaction of the

[1] Axelrod (1997) recommends that assumptions underlying an agent-based model should be as plain as possible and thereby the complexity only lies in the simulated results.

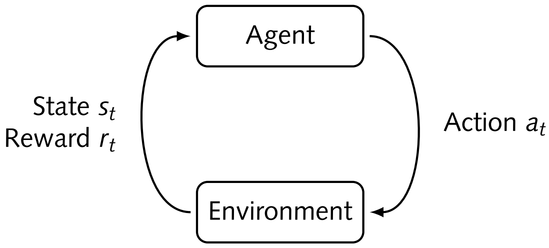

Figure 3.4 | Reinforcement learning. The agent knows the current state s_t of the environment and has an expectation about the reward any action a_t achieves in this state. After the agent selects an action a_t^*, he receives the reward r_t and is informed about the new state s_{t+1} of the environment. The realized payoff r_t serves to adjust the agent's expectation associated with the selected action. In the next step, the agent chooses another action a_{t+1}^* based on the expected rewards of all possible actions.

agents without external interference. At the end, the results can be carefully analyzed and checked for potential inconsistencies.

A particular strength of agent-based models is that they are able to replicate imperfect competition (Tesfatsion, 2002), which is often found in the context of oligopolistic electricity markets, e.g., in Germany, where in 2011 four corporations—EnBW, E.ON, RWE, and Vattenfall—possessed about 80 % of the thermal generation capacities (Bundeskartellamt, 2011). For this purpose, strategic bidding can be implemented. In repeated interactions, agents that possess market power choose their markup level using dedicated algorithms capable of taking the current state of the market into account (Bunn and Oliveira, 2001). The ability to predict the behavior of agents in new environments through machine learning is a valuable complement to existing approaches in which learning is often neglected or cannot be modeled (Roth, 2002). Among the numerous methods of machine learning, the algorithms mainly used in the context of simulating electricity markets, rely on reinforcement learning (see Figure 3.4), such as Roth-Erev- (Roth and Erev, 1995) or Q-Learning (Watkins and Dayan, 1992).

Agent-based models offer great flexibility, for example, additional agents can be added quickly, and the properties of existing agents, e.g., the ability to learn or the rules for interaction, can be conveniently adapted (Jennings, 2000). Thereby, the influence of the various actors can be made visible even if learning algorithms are only partially considered. In addition, agents can easily be modeled in different levels of detail or as aggregated entities. On the flipside, for modelers, who have to determine the level of detail, this also presents a major challenge, and often the process remains an art more than a science (Bonabeau, 2002).

Whereas optimization models aim to find the best value for their objective function, the outcome in agent-based models emerges from the interaction of all actors and does not necessarily correspond to an overarching target, for instance, the cost-minimal solution. However, it is possible to rely partly on algorithms, which have a much lower computational complexity (An, 2012). This offers the advantage that despite the explicit consideration of detailed techno-economic restrictions, a comparatively short runtime can be realized, which renders the use of common simplifications used for optimization models, such as representative days, superfluous (Nahmmacher et al., 2016; Poncelet et al., 2016).

Another challenge in the development of an agent-based model is that human behaviors need to be incorporated often, and thus potentially irrational actions or subjective decisions are integrated, so-called soft factors that are often difficult to calibrate, quantify or justify (Bonabeau, 2002). As a result, model results may to some extent be challenging to predict and interpret, as they strongly depend on the initial state of the system and the complex interaction of the agents.

To facilitate the model creation, there are various agent-based software libraries, such as the widely used Repast (Argonne National Laboratory, 2017) or MASON library (George Mason University, 2017), which allow to create different agents, specify their relationships or visualize the results for different applications. Often, however, advanced programming skills are still required for their use (Zhou et al., 2007). Solutions tailored specifically for electricity systems are also available: AMES (Li and Tesfatsion, 2009), EMLab (TU Delft, 2017), SEPIA (Harp et al., 2000) or MASCEM (Vale et al., 2011). When deciding on a solution, however, it must be taken into account that not all models are still actively developed, and some older versions are even no longer publicly available.

3.3.3 Game-theoretic models

Game-theoretical models aim to derive optimal strategies for intelligent, rational decision-makers and examine the resulting equilibrium states.[2] For this purpose, mathematical games are defined in which each player selects a strategy from a set of predefined strategies. Each strategy is then assigned a value by means of a payout function depending on the strategies chosen by other players. If each player has chosen a strategy and no player has an incentive to deviate from his strategy while the other strategies remain unchanged, a Nash equilibrium is reached (Osborne and Rubinstein, 1994).

In the field of electricity market modeling, it is possible to classify the most common game-theoretic approaches into Bertrand, Cournot, and Supply-Function-Equilibrium models (Li et al., 2011a). These models are particularly well suited for analyzing the exercise of market power by strategic players assuming oligopolistic competition. In each model, it is assumed that players make their decisions simultaneously. Whereas in Cournot competition, players compete in quantity, in the Bertrand model there is competition for the price. In contrast, in the Supply-Function-Equilibrium model, players compete both in terms of quantity and price by choosing a strategic supply function (Bolle, 1992). However, simplifications are frequently required, and thus essential technical properties, such as downtimes or minimum operating times of power plants, are ignored (Genoese, 2010). Consequently, it is oftentimes not possible to examine existing markets adequately. However, descriptive case studies can be carried out in which qualitative results are of primary importance, and quantitative results only have a limited significance (Weber, 2005). For this reason, these types

[2] For a detailed overview of the application of game-theoretic models to electricity markets, see Bajpai and Singh (2004) or Hobbs (2001).

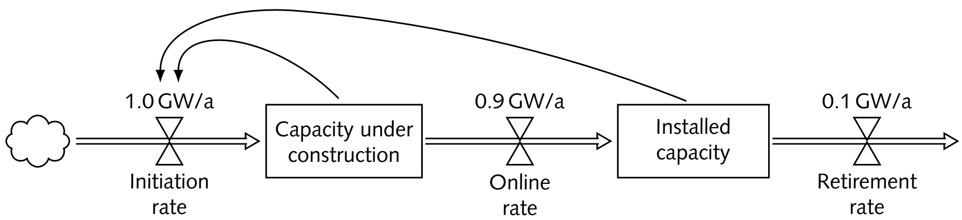

Figure 3.5 | Capacity stocks and flows in a system dynamics model. This diagram shows an exemplary flowchart (cf. Ford, 1997), in which the stocks ("capacity under construction" and "installed capacity") describe the current state of the system and are used as the basis for deriving decisions as well as actions, for example, the initiation rate. The rates, on the other hand, describe the actions in the system, which in turn cause changes to the inventory levels (Pereira and Saraiva, 2011).

of models are used primarily for providing policy advice and scarcely used in the industrial sector (Möst and Keles, 2010).

3.3.4 System dynamics models

The first system dynamics models were developed in the 1950s by Forrester (1961), who analyzed the dynamic behavior of complex systems and thereby obtained the following central insight: In order to determine the behavior of a system, the sometimes time-delayed relationships between its different interlocking components are often just as relevant as these components themselves. Furthermore, new structures and unknown behavior often occur as an emergent phenomenon, which cannot be explained by the individual analysis of all components but can only be understood in the overall context of the system (Goldstein, 1999).

System dynamics is utilized in a variety of different domains, e.g., for the modeling of technical simulations, business processes or even for the analysis of social behavior (Forrester, 1987). The electricity sector has some characteristics, such as the presence of strategic behavior or market imperfections, which are particularly well suited for system dynamics (Pereira and Saraiva, 2011). As a result, for example, national energy policy measures, investment decisions under uncertainty or the liberalization of the electricity sector were studied using system dynamics models (Qudrat-Ullah, 2013).

A current overview of the different applications in the electricity sector can be found in Ahmad et al. (2016).

For the creation of a system-dynamic model, a variety of toolkits is available, which considerably simplify the process via a visual interface (Rizzoli and Young, 1997). Among the most popular products are STELLA (Isee systems, 2017), Vensim (Ventana Systems, 2017) or Simulink (Mathworks, 2017). On the one hand, these proprietary tools provide rapid access for users who have expert knowledge in their field but are unfamiliar with the mathematical concepts of the system dynamics approach. On the other hand, the user's ability to perform extensive customizations is limited.

The behavior of a system dynamics model and likewise the quality of the model results is considerably influenced by the defined feedback loops (see Figure 3.5), whose validation and calibration is a central challenge and a frequent point of criticism (Oliva, 2003). Another difficulty is that feedback loops do not allow to model the decisions of individual agents or the ability to learn from experience (Schieritz and Milling, 2003).

3.3.5 Financial models

Financial mathematical models (also quantitative, stochastic or reduced-form models) attempt to identify and capture the so-called stylized properties of electricity prices preferably through analytical formulas. These properties, i.e., price spikes and correlations with other processes such as the oil or gas price, can be considered universal as they are shared by the majority of the electricity spot markets (Carmona and Coulon, 2014; Weron, 2006). Consequently, neither a supply or demand function is defined, whose point of intersection lead to an equilibrium price, but rather the number of factors and parameters is reduced to a minimum.

For this purpose, approaches originally developed for the modeling of interest rates or the price dynamics of commodities are used, where, analogous to the electricity price, it is often assumed that their values fluctuate and return to a long-term average, which is also referred to as mean reversion (Geman and Roncoroni, 2006). For this purpose, the price development can be characterized by, e.g., an Ornstein-Uhlenbeck process (Benth et al., 2007). In addition, to reflect the seasonal factors and the occasional price jumps typical for electricity prices, for example, deterministic functions or Poisson processes can be applied (Cartea and Figueroa, 2005).

In the field of financial mathematical models, a distinction is commonly made between the modeling of spot (Keles et al., 2013) and future prices (Fleten and Lemming, 2003). One reason for the popularity of this type of model is that the comparatively plain structure often leads to theoretical developments, which can be verified against empirical data (Carmona and Coulon, 2014). These models are used in particular for risk management purposes or the pricing of derivatives, but usually not for short-term price forecasts.

3.3.6 Econometric models

Econometric (or statistical) approaches are used to model the price of electricity by establishing a mostly additive or multiplicative mathematical relation[3], between its historical values and related exogenous variables such as the load, temperature, time of day or different fuel prices (Aggarwal et al., 2009). This is based on the assumption that the electricity price can be expressed by either the product or the sum of different components. Once a model has been formulated, its parameters must be estimated using statistical estimation methods, for example, the method of moments, the Bayesian method or the method of maximum likelihood. In the latter, probably the most widely employed method, the parameters are chosen in such a way that the probability to observe the occurring historical values is maximized (Box et al., 2008).

In the forecasting of electricity prices, econometric approaches enjoy wide interest

[3] In economics, other mathematical relations, for example, a logarithmic relationship, can also be assumed, as it is the case in the logit model (Harrell, 2015). In predicting bank failure (Martin, 1977) or the likelihood of a homeowner defaulting on a mortgage (Campbell and Dietrich, 1983), this approach is widespread, but it is not the case for modeling the electricity sector.

as these, on the one hand, allow for an intuitive understanding of the individual price factors[4] and, on the other hand, existing knowledge, e.g., about the forecasting of the load or wind feed-in, can be integrated (Möst and Keles, 2010). However, a common point of criticism is that non-linear behavior, such as price spikes, can only be reproduced to a limited extent. Nevertheless, for practical applications, the quality of econometric approaches is comparable to others as non-linear behavior occurs only rarely (Weron, 2014).

3.4 Model selection and further research needs

Based on the requirements mentioned in this chapter and the model properties described subsequently, in the next sections, on the one hand, a model is selected, and, on the other hand, the key challenges, which have to be addressed for the future development of energy system models, are outlined.

3.4.1 Model comparison and selection

Econometric or financial mathematical models are primarily well suited for specific purposes, i.e., for the forecasting of the electricity price or the valuation of derivatives. However, they are only of limited use for analyzing further related aspects, such as the effects of a strategic reserve or the development of CO_2 emissions, as they do not take into account significant technological and economic constraints. Therefore, these models are not fully capable of reproducing the essential characteristics of electricity markets or the behavior of the market participants (Ventosa et al., 2005).

Game-theoretical models focus on the strategies of the players and the resulting market equilibria. However, in this context, qualitative results are of primary concern (Weber, 2005), such as the existence of market power (Prabhakar Karthikeyan et al.,

[4] For example, regression models with static (Bublitz et al., 2017; Cludius et al., 2014; Würzburg et al., 2013) or time-variable coefficients (Paraschiv et al., 2014) are frequently used to examine the merit order effect.

2013). The dispatch of power plants is not simulated, which restricts the range of application and thus does not provide any information on, for example, the energy consumption. However, often game theoretical concepts are used in agent-based models (Weiss et al., 2002), which makes a proper distinction between these two model classes quite problematic. This is further exacerbated by the fact that the terminology is not always used coherently in literature.[5]

Fundamental models such as system-dynamics-, optimization, and agent-based models offer a wide range of potential applications by simulating the essential elements of electricity systems. The benefit of being able to analyze the influence of these fundamental elements, however, comes with a high level of effort—for instance, a substantial amount of input data is required. Nonetheless, in order to understand the interaction of the individual components of a system, it is necessary to represent and analyze them explicitly.

Whereas in the past, in many existing models only techno-economic aspects are considered, the social acceptance of technologies has gained an increasingly important role as well as the involvement of stakeholders such as community groups or non-governmental organizations in decision-making processes (Droste-Franke et al., 2015). In addition, an increasing number of participants in the electricity market such as households, who traditionally acted purely as consumers, take on the role of a so-called prosumer who not only purchases electricity but also generates, stores, or directly consumes it (Grijalva and Tariq, 2011). Viewing the electricity sector from the perspective of a central planner who maximizes economic welfare in the system as in the case of optimization models, thus, does not appear to be expedient. However, this is a key strength of agent-based models, which are able to integrate individual actors and strategic behavior directly. Nonetheless, the flexibility of agent-based models also allows using optimization techniques for the individual decisions of the agents.

[5] For instance, Vries and Heijnen (2008) refer to their model as a system dynamics model, although the more appropriate term seems to be agent-based in regard to the accompanying model description.

Table 3.2 | Characteristics of optimization and agent-based models for electricity systems and markets. Through the use of agent-based and optimization models, an in-depth understanding of energy industry issues can be developed. Both approaches have different advantages and disadvantages; thus, complement each other. *Sources:* Genoese (2010); Möst and Fichtner (2008).

Model approach	Agent-based models	Optimization models
Model objective	Realistic simulation of the development of the market, e.g., wholesale prices	Determination of the optimal outcome under a given objective
Market perspective	Real, imperfect markets with actors who behave strategically	Markets with perfect competition and complete transparency
Information	Myopic and imperfect	Myopic or complete (perfect foresight)
Market prices	Result of supply and demand, including possible mark-ups	Marginal costs of electricity demand (shadow price)
Strengths	Considering strategic behavior and imperfect information, well extensible and adaptable	Optimal results, established methodology, transparency through concise mathematical notation
Weaknesses	Decision rules determine outcome but in some cases hard to validate	Deviations between optimal results and real market events, neglecting of the participants' perspectives

A comparison of the most important characteristics of both types of models can be found in Table 3.2.

By integrating the perspective of an actor, as Farmer and Foley (2009) argue, a wider range of non-linear behavior, e.g., sudden shocks, can be represented, thereby allowing decision-makers to simulate and assess the impact of a range of policies on an economic system under different future scenarios. However, it should also be noted that the integration of a stakeholder perspective presents new challenges. Due to the lack of publicly accessible data, in particular the parameterization of the various agents is based on assumptions that are difficult to verify.

A further advantage of agent-based models is the ability to create a model of high-temporal resolution, which avoids significant deviations that could result from a simplified temporal representation often found in optimization models (Frew and Jacobson, 2016; Poncelet et al., 2016). System dynamics models are able to model the essential elements of the electricity sector and can be used flexibly. However, determining the flow rates is a major challenge and the lack of an option to represent individual actors is a compelling argument for the agent-based approach chosen for this work (Oliva, 2003; Schieritz and Milling, 2003).

3.4.2 Central challenges

In the following, the central challenges that energy system models face due to the transforming framework conditions are addressed. In this context, it is imperative to consider the increased complexity of the energy system by taking into account the development of different uncertain influences, such as the future volume and flexibility of electricity demand. In addition, detailed model validations need to be carried out, and transparency should be increased by clearly communicating existing model limitations.

Complexity and transdisciplinarity

Energy systems are becoming increasingly complex and decentralized, in part due to the transition from large thermal power plants to a wide range of renewable energy sources, which often renders approaches from the past insufficient to adequately represent the future energy system.

In addition, energy systems have complex dynamic properties such as feedback loops and lock-in effects, which are not represented by simplified decision rules based solely on minimizing system costs. Even if complex modeling approaches entail many challenges, they are able to yield new valuable insights, where other applying modeling approaches produce over-simplified answers (Bale et al., 2015).

Furthermore, critical influencing factors such as social justice, politics, and unforeseen technological advances are not adequately considered in most of the existing models (Gilbert and Sovacool, 2014; Jefferson, 2014; Sovacool, 2014). The widespread use of these models and the lack of alternatives lead to the fact that often purely technological solutions are presented on energy-economic questions. However, the social processes determining their acceptance and use are disregarded (Spreng, 2014). The analysis of future energy systems, therefore, requires a broader collaboration between technical, economic and social sciences in order to better assess and predict actual developments (Sovacool et al., 2015).

Uncertainty

Uncertainty can generally be classified as parametric and structural uncertainty, whereby the former refers to the uncertainty regarding the input data and the latter refers to the limited ability to represent reality through a model (Hunter et al., 2013). In models, usually only parametric uncertainty is regarded, as it is almost impossible to thoroughly address structural uncertainty (Pfenninger et al., 2014).

There are different ways to address the effects of parametric uncertainty, depending on whether the model is deterministic, i.e., identical assumptions always lead to identical results, or stochastic, i.e., identical assumptions may lead to diverging results. With deterministic models, it is possible to include parametric uncertainties by varying the input parameters of the model and analyzing their effects on the result (Monte Carlo method). In stochastic models, such as stochastic optimization models, uncertainties can be directly integrated into the model, e.g., by replacing a single parameter with its mean value and variance (Mancarella, 2014; Wallace and Fleten, 2003).

Applying a Monte Carlo simulation is a comparatively basic way to integrate uncertainty. Usher and Strachan (2012) show that gained results can be structurally different from stochastic models. Even though stochastic models are more challenging to create and apply than deterministic ones, they are required to adequately deal with the evolving uncertainties in the energy sector (Strachan, 2011). However, as these models still have limitations, it is important to communicate inherent assumptions concerning the integration of risks in the presentation of results (Bale et al., 2015).

Validation

Economic models differ from physical models in the respect that no natural scientific phenomena, which remain constant over time and space, are investigated. The focus is rather on the interaction of market players whose actions are only partially observable and whose objectives as well as assumptions are not known publicly. Thus, models of the electricity market cannot be validated in the same way as physical models (DeCarolis et al., 2012). Nevertheless, in order to identify possible divergences from real-world systems, model results need to be compared with historical values so that any divergence can be taken into account and results can be interpreted in a more meaningful way (Fagiolo et al., 2007), which in most cases is only carried out insufficiently. Furthermore, it would be helpful to define a standardized use case with which better comparability of the different models can be reached. For this purpose, the initiatives Open Power System Data (2017) and the Open Energy Modelling Initiative (2017) are first promising steps.

Transparency

In the past, energy system models have been criticized for being intransparent or even for representing a black box for external parties. As the methodology of a black box model cannot be understood and comprehensively verified, society or decision-makers must have confidence in the model's abilities. However, if inconsistencies arise, trust can vanish quickly (Loken, 2007). Furthermore, intransparency contradicts the scientific method, where the reproducibility of results and evaluation are essential.

Non-transparent modeling can lead to poor decisions with far-reaching consequences. As described by Pfenninger (2017), in the preparation of the EU Energy Roadmap, opaque and overly optimistic assumptions for onshore wind power in the UK have influenced the national legislation and may have delayed the decarbonization of the British energy sector. Such and similar events explain the call of Acatech et al. (2015) to make the source code of energy system models as well as all input data publicly available. In practice, however, this is proving to be difficult, first and foremost, due to trade secrets or security concerns over critical infrastructure data. Another recommendation is to review the source code of the models to further improve its quality and eliminate errors. Although most of the studies and models do not yet meet the demands for more transparency, several open source initiatives have already been established in recent years, e.g., EMLab (TU Delft, 2017) or OSeMOSYS (Howells et al., 2011), the former being an agent-based model family and the latter an optimization model. In addition, Open Power System Data (2017) provides scientists with access to an open database containing, for example, techno-economic data on power plants or time series of the feed-in of renewable energies.

Chapter 4

An analysis of the decline of electricity spot prices in Europe: Who is to blame?

European electricity markets are currently going through a phase of transition, which is shaped by three key factors: The expansion of renewable energies, especially wind power and photovoltaics, the phase-out of nuclear energy and the European market integration.

Different promotion schemes were installed in European countries to support the expansion of renewable energies. Germany as a leading country in the promotion of renewable energy already introduced its first renewable energy law ("Stromeinspeisegesetz," Bundesregierung, 1990) in 1991. This law is regarded as the first feed-in law worldwide and marked the start of a tremendous rise of renewable energies. In 2000, technology-specific feed-in tariffs were established, as most renewable energies have not been able to undercut the costs of conventional fossil-fueled power plants. These tariffs guaranteed a fixed price for all electricity generated in a predetermined period that is paid by the transmission system operators who pass on the costs to the end consumers (German Renewable Energy Sources Act, Bundesregierung, 2000). In 2015, renewable energies contributed with 195.9 TWh (about 30 %) to the electricity generation, which compared to 2005 corresponds to an increase of 213 % (BMWi, 2016c). Among the different renewable energy sources, wind is currently the most important source of energy production with a share of 44.9 % followed by biomass (22.6 %) and photovoltaics (19.6 %). However, considering entire Europe, hydropower still has the largest share with 45.4 % mainly due to the electricity production in the Alpine and Scandinavian countries (European Commission, 2015).

A major advance for the integration of the European electricity markets represents the market coupling in Central Western Europe (Benelux, France, and Germany) at the EPEX SPOT, which started on November 9, 2010 (EPEX SPOT, 2016). About three years later, market coupling was extended to also include North-Western Europe (NWE). Through market coupling, generation capacities can be used more efficiently across borders and market participants profit from welfare gains (Weber et al., 2010). As long as sufficient interconnecting capacities between neighboring countries are available, wholesale prices in coupled markets converge, leading for instance to identical day-ahead market prices in Germany and France in about 27 % of the time in 2015.

In the last years, the transition of the German electricity market was accompanied by a strong price decline for base as well as peak wholesale prices (see Figure 4.1). In 2011, the yearly base price corresponded equal to 51.12 EUR/MWh but dropped to 31.63 EUR/MWh in 2015, a decrease of roughly 38 %. Electricity generators have been profoundly affected by these developments, even more so as no capacity remuneration market is currently implemented in Germany. Many power plants are facing diminishing return. Currently, the decommissioning of 9 GW of thermal capacities within the next years is expected (BNetzA, 2016c), stirring up concerns about generation adequacy.[1] In order to safeguard the transition phase of the electricity market and to guarantee security of supply, the German government decided to implement a capacity reserve that will be procured in December 2016 (BMWi, 2015). Investment decisions in a changing market with major uncertainties are challenging and certainly not all market participants expected the ongoing price decline. E.ON, for example, decided in 2008 to build a state-of-art gas-fired power plant (Irsching 5) with an efficiency of 59.7 % and forecasted more than 4000 yearly operating hours (Thom-

[1] As power plant owners are not obliged to explain the reasons for a decommissioning, it not clear to which extent the decisions are based on economic or technical reasons.

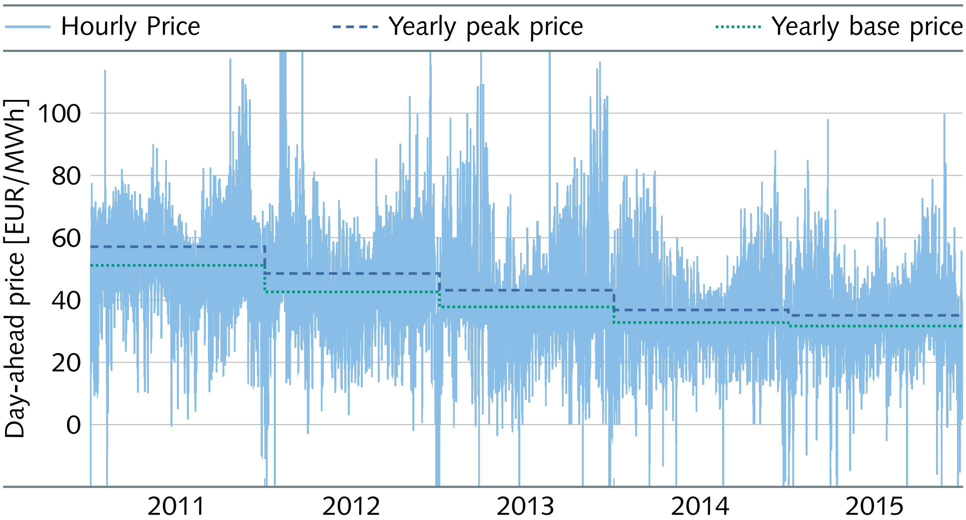

Figure 4.1 | The day-ahead market prices for the German/Austrian market zone. The development of base and peak prices shows a clear trend. Since 2011, annual averages have fallen, with the decline slowing down recently. From 2011 to 2012 the base prices dropped by 8.53 EUR/MWh, from 2014 to 2015 the reduction was 1.13 EUR/MWh, which indicates a stabilization of the market. Also, the difference between base and peak prices, which in 2011 amounted to 6.00 EUR/MWh, has decreased to 3.43 EUR/MWh in 2015. *Source:* EPEX SPOT (2018b).

son Reuters, 2013). However, on April 1, 2016, the power plant was scheduled to be decommissioned due to economic reasons (Uniper, 2016).[2]

In the public perception and many political discussions, the blame for the current price slide and the related developments is shifted to the expansion of renewable energies, which have been strongly fostered by financial subsidies. Additionally, in the recent academic discourse, there is a broad spectrum of research that focuses on the impact of the promotion of renewable energies, but only few studies have been undertaken to analyze the impact of other factors on wholesale electricity prices. Therefore, this chapter contributes to the academic discussion by providing a quantitative anal-

[2] Already in 2012, Irsching 5 achieved only half of the expected yearly operating hours (Thomson Reuters, 2013) and became part of a reserve for redispatch measures until 2016. Afterward, the power plant was supposed to be decommissioned. However, this decision is currently facing a ban from the regional transmission system operator (TSO) due to security and reliability of supply concerns.

ysis of the fundamental price drivers and their impact on the recent decline in the German wholesale electricity prices, which also can be observed in other European markets such as France, Italy or Spain. To understand also the future effect of these price drivers on electricity prices and power plant investments, different scenarios for the development of price drivers until 2020 are generated and applied. These scenarios allow on the one hand to understand, how strongly electricity prices can vary in 2020, and on the other hand to assess the economic feasibility of power plant investments, especially that of gas power plants. For this reason, in the final step, based on a net present value (NPV) approach, an economic evaluation of a state of the art power plant with a combined cycle gas turbine (CCGT) similar to Irsching 5 is carried out.

The remainder of this chapter is structured as follows. In Section 4.1, selected studies on price drivers in electricity markets are discussed. In the next section, the methodology is described, and three different models are presented. Section 4.4 then shows an analysis of the main price drivers in the German electricity market. Finally, in Section 4.5 the results are summarized and a conclusion is presented.

4.1 Literature review

In this section, an overview of previous studies is shown that analyzes the influence of fundamental factors on electricity prices. In these studies, a wide range of models[3] is utilized. According to Aggarwal et al. (2009), electricity market models can be classified into game theory, simulation and time series models. Game theory models often focus on the strategies of the market players, simulation models create a detailed representation of the electricity system and time series models use historical data of the dependent variable. As there does not exist any study within the mentioned scope that utilizes a game theory model, in the following, only a distinction between simulation and time series models is made.

[3] A recent discussion and outlook on electricity price modeling can be found, e.g., in Weron (2014).

In line with the rise of renewable energies, many of the recent studies focus on the effect of wind and photovoltaics on the electricity price, the so-called merit-order effect (Sensfuß et al., 2008), and do not discuss the impact of fuel price changes or changing import/export flows. Furthermore, as Würzburg et al. (2013) point out, it must be kept in mind that the comparability of studies regarding the merit-order effect is limited due to the heterogeneous approaches, e.g., different sets of included fundamental variables (e.g., fuel prices, market scarcity), alternate scope (inclusion of neighboring countries or emission trading systems) and varying scenarios (no changes or alternative capacity expansion paths). An overview on the selected literature can be found in Table 4.1.

Table 4.1 | Studies on influence factors of the electricity price. With regard to the geographical focus, Europe is at the center of interest and, regarding the influence factors, most studies analyze the effects of wind and photovoltaics. The studies in the table are listed in alphabetical order.

Study	Methodology	Regional scope	Time period	Focus and key findings	Results (EUR/MWh)		Reference point
Bode and Groscurth (2006)	Simulation	Germany	2005	Impact of renewables; price reduction depends on the level of the installed renewable capacity	RES (Elastic demand)	−0.55	GW inj.[a]
					RES (Inelastic demand)	−0.61	GW inj.[a]
Cludius et al. (2014)	Time series	Germany	2008–2016	Effect of wind and solar, Energy-intensive industry profits from low electricity price due to welfare transfers	2010–12 Wind	−1.07	GW inj.[a]
					2010–12 PV	−1.14	GW inj.[a]
					2016 Wind+PV	−14 to −16	Scen. vs. None[e]
Dehler et al. (2016)	Time series	Switzerland	2011–2015	Price influence of neighboring countries; even though no large gas-fired power plants are installed in Switzerland, gas price drives electricity price which is explained by the important role of gas in the Italian market	Gas coefficent Summer	0.25	GW inj.[a]
					Gas coefficent Winter	0.81	GW inj.[a]

Study	Methodology	Regional scope	Time period	Focus and key findings	Results (EUR/MWh)		Reference point
Ederer (2015)	Simulation	Germany	2006–2014	Impact of offshore wind; similar impact of on- and offshore wind on market prices, offshore wind imposes less variability on market price	Wind onshore short-term	−0.56	TWh y. g.[b]
					Wind offshore short-term	−0.75	TWh y. g.[b]
					Wind onshore long-term	0.11	TWh y. g.[b]
					Wind offshore long-term	−0.19	TWh y. g.[b]
Gelabert et al. (2011)	Time series	Spain	2005–2010	Impact of renewables; decreasing trend in the estimated magnitude of merit-order effect		−3.80	GW inj.[a]
					RES 2005	−3.40	GW inj.[a]
					RES 2006	−1.70	GW inj.[a]
					RES 2007	−1.50	GW inj.[a]
					RES 2008	−1.10	GW inj.[a]
					RES 2009	−1.70	GW inj.[a]
					RES 2010		
Hirth (2018)	Simulation	Germany/Sweden	2008–2015	Drop in spot prices; most important drivers in Germany/Sweden is the increase of renewable generation, followed by the carbon prices respectively the demand	RES (DE)	−15.80	2008 vs. 2015
					Carbon (DE)	−12.50	2008 vs. 2015
					RES (SE)	−19.90	2010 vs. 2015
					Demand (SE)	−18.20	2010 vs. 2015
Kallabis et al. (2016)	Simulation	Germany	2007–2014	Decline of futures prices; carbon emission allowances price most important driver of futures electricity prices	Carbon	−14.14	2007 vs. 2014
					Wind and PV	−6.28	2007 vs. 2014
O'Mahoney and Denny (2011)	Time series	Ireland	2009	Effect of wind; savings from wind-generated electricity are greater than subsidy over regarded time period	Wind	−9.90	GW inj.[a]
O'Mahoney and Denny (2013)	Time series	Ireland	2009	Generator behaviour, Electricity market seems to be efficient, Gas is price driver, coefficients of coal and oil price are not significant	Gas coefficent	0.55	GW inj.[a]

Study	Methodology	Regional scope	Time period	Focus and key findings	Results (EUR/MWh)		Reference point
Paraschiv et al. (2014)	Time series	Germany	2010–2013	Effect of wind and solar; merit-order effect differs among hours of the day due to changing demand, coal as well as gas price has a strong effect in hours with a typically higher demand, e.g., 12 and 18	(Results only shown in figures)		
Sensfuß et al. (2008)	Simulation	Germany	2001, 2004–2006	Impact of renewables; merit-order effect exceeds the volume of the net support payments	RES 2001 RES 2004 RES 2005 RES 2006	−1.70 −2.50 −4.25 −7.83	Hist. vs. N.[c] Hist. vs. N.[c] Hist. vs. N.[c] Hist. vs. N.[c]
Sensfuß (2013)	Simulation	Germany	2011–2012	Impact of renewables; energy-intensive industry profits from low prices due to lower levys	RES 2011 RES 2012	−8.72 −8.91	Hist. vs. S.[d] Hist. vs. S.[d]
Thoenes (2014)	Time series	Germany	2011	Impact of nuclear moratorium; future prices adjusted by 6 GW shut down, shortly afterward less	(No results in EUR/MWh)		
Traber and Kemfert (2011)	Simulation	Germany	2007–2008	Effect of wind; wind reduces profitablity of gas-fired power plants	Wind	−3.70	Hist. vs. N.[c]
Traber et al. (2011)	Simulation	Germany	2020	Impact of RES; slight increase of EEG levy expected in 2020	RES	−3.20	2010 vs. 2020 S.
Weber and Woll (2007)	Simulation	Germany	2006	Effect of wind; merit-order effect depends on the regarded time horizon	Wind (short-term) Wind (medium-term) Wind (long-term)	−4.04 0.40 1.00	Hist. vs. N.[c] Hist. vs. S.[d] Hist. vs. S.[d]
Weigt (2009)	Simulation	Germany	2006–2008	Effect of wind; wind capacity cannot significantly reduce required fossil capacities	Wind 2006 Wind 2007 Wind 2008	−6.26 −10.47 −13.13	Hist. vs. N.[c] Hist. vs. N.[c] Hist. vs. N.[c]

Study	Method-ology	Regional scope	Time period	Focus and key findings	Results (EUR/MWh)		Reference point
Würzburg et al. (2013)	Time series	Germany, Austria	2010–2012	Effect of wind and solar; German nuclear exit did not affect merit-order effect, price effect of wind and solar are similar	Wind and PV	–1.00	GW inj.[a]

[a] Per GW injection.
[b] Per TWh yearly generation.
[c] Historical generation versus no generation.
[d] Historical generation versus alternative scenario generation.
[e] Scenario generation versus no generation.

Simulation models

One of the first studies of the merit-order effect is carried out by Sensfuß et al. (2008), who use an agent-based model of the German electricity market to analyze the effect of electricity production from wind power and photovoltaics on the day-ahead electricity price. They determine an average price reduction for the year 2001 of 1.70 EUR/MWh and for the years from 2004 to 2006 a reduction of 2.50 to 7.83 EUR/MWh. In another study, Sensfuß (2013) applies the same model and calculates a price reduction of 8.72 EUR/MWh and 8.91 EUR/MWh for 2011 and 2012 respectively. In this analysis, the electricity production of biogas and biomass is considered as well as additional capacities of coal and gas-fired power plants in the scenario with no renewable production.

Bode and Groscurth (2006) take a rather simplistic approach by calculating the intersection of the electricity demand and supply curve under the assumption of perfect competition and static daily demand profiles for each month. They show that the price reduction depends on the level of the installed renewable capacity and quantify the effect in the case of an elastic demand at 0.55 EUR/MWh per GW and in the case of a nearly inelastic demand at 0.61 EUR/MWh per GW.

Using a fundamental merit-order model of the German electricity system that separates between 34 different power plant types, Weber and Woll (2007) find that in 2006 the feed-in of wind leads to a short-term price reduction of 4.04 EUR/MWh when compared to a scenario with no wind feed-in. However, if the wind capacity is replaced by alternative hypothetical power plants, they expect a medium-term price effect of −0.40 EUR/MWh and long-term effect of −1.00 EUR/MWh.

In another study, Weigt (2009) carries out an analysis of the effects of wind energy by applying a model of the Germany electricity market that minimizes unit commitment, start-up and marginal costs without taking into account cross-border flows. Although the results show that the installed capacity cannot significantly reduce fossil capacities, it, however, does reduce the average wholesale market price. In line with the growing wind capacity, the price reduction from to 2006 until mid-year 2008 is estimated to range from 6.26 to 13.13 EUR/MWh. Based on the work of Traber and Kemfert (2009), Traber and Kemfert (2011) apply an optimization model (ESYMMETRY) to analyze the impact of wind energy in Germany. Compared to the prices of a counterfactual scenario with no wind feed-in, the historical wholesale electricity prices from winter 2007 to autumn 2008 are on average 3.7 EUR/MWh higher. In a subsequent study, Traber et al. (2011) compare two scenarios for the German electricity market in 2020, one baseline scenario with an expansion of renewable capacities and one scenario with no further expansion of renewable capacities but increased coal power plant capacity. Here, the additional electricity production of renewable energies is expected to lead to a price reduction of 3.2 Euro/MWh.

Ederer (2015) analyzes the historical and expected impact of offshore wind in Germany from 2007 to 2019. Instead of constructing a detailed fundamental model, they use original market data for ask and the supply bids and implement the market clearing algorithm used at the EPEX SPOT. For scenarios with additional wind capacity, a short and a long-term effect are incorporated, i.e., additional electricity supply bids at low variable costs and the replacement of base-load capacity. The simulation suggests that on short-term decreasing prices are related to the excess of supply, but on long-term market average prices do not change due to additional wind generation as base-load power plants are replaced. However, due to the limited availability of wind compared with thermal capacities, the electricity price shows increased volatility.

Contrary to most studies that focus on the day-ahead market, Kallabis et al. (2016) introduce a parsimonious model for the electricity futures market and analyze the development of the German futures prices from 2007 to 2014. They obtain the result that the volatile carbon emission allowances price was by far the most important driver of electricity prices with an effect of 14.26 EUR/MWh – more than the combined impact of changes triggered by the demand, renewables and fuel prices (10.05 EUR/MWh). However, according to their results, the overall contribution margin of the power plants was affected the most by the regressing demand followed by the increasing electricity production from renewables. Moreover, they find that the effect of the carbon price on the margins is twofold, whereas gas-fired and nuclear units face decreasing margins, the more carbon-intensive technologies such as coal and lignite-fueled power plants could increase their profits.

Time series models

In contrast to the previous studies that represent the electricity system by using bottom-up modeling approaches, the articles presented in following paragraphs rely on econometric concepts, especially regression models to analyze the drivers of wholesale electricity prices.

O'Mahoney and Denny (2011) develop an hourly multiple linear regression model for the Irish electricity market. They find that in 2009 the electricity price is 12 % lower due to electricity generation from wind and with additionally installed wind capacity the electricity price decreases by 9.9 EUR/MWh per GW. In a subsequent study, in order to analyze the generator behavior in the Irish electricity market, O'Mahoney and Denny (2013) construct a multiple linear regression model with a set of variables that includes the fuel/carbon prices, the marginal capacity and the net demand that is covered by the conventional supply. They apply the model to hourly data from 2009 and show that the Irish price mainly depends on the gas price, the net demand and the marginal capacity. The coefficients of coal and oil price are not significant which they explain by the fact that in Ireland about 60 % of the conventional capacities consist of gas-fired power plants. Additionally, the model is run as a separate regression for each hour of the day, which improves the results and shows that the influence of fuel prices is time-dependent.

In another piece of research, Würzburg et al. (2013) analyze the effects of the electricity generation of photovoltaics and wind for the German–Austrian market area via a multiple linear regression model that amongst others includes the load, gas price, and cross-border flows. With data from July 2010 to June 2012, they quantify the impact of the wind and photovoltaic feed-in at about 1 EUR/MWh per GWh, which they describe as counterintuitive as the photovoltaic feed-in correlates typically with a higher demand contrary to the wind feed-in. Moreover, the decommissioning of about 7 GW of nuclear capacity did not alter the price reduction of wind power and photovoltaics. Interestingly, in their results, the coefficient of the import-export electricity is insignificant even though exports changed drastically subsequently to the decommissioning of nuclear power plants in 2011.

Cludius et al. (2014) analyze the distributional effects of the rising renewable generation for different types of electricity customers by developing a multivariate regression model of the electricity price similar to Gelabert et al. (2011). They find that the electricity generation by photovoltaics and wind has reduced the electricity price by 6 EUR/MWh in 2010 and 10 EUR/MWh in 2012, which energy-intensive industries benefit from as, in contrast to private households, the industries cover only a small share of the passed through charges. Additionally, they carry out a prognosis for 2016 and estimate the price reduction to be around 14 to 16 EUR/MWh, depending on the different regarded expansion paths of renewable energies.

In a recent analysis, Dehler et al. (2016) focus on the Swiss electricity market and its interdependencies with neighboring countries in the timeframe of 2011 to 2014. For each hour of the day, they apply a multiple linear regression model and show that during summer the electricity price and the feed-in from renewables in Germany affect the Swiss price although during winter, peak load situations in Italy and France are correlated with high prices on the Swiss market. Even though no large gas-fired power plants are installed in Switzerland, their results show the gas price influences the Swiss price with a coefficient of 0.25 EUR/MWh and 0.81 EUR/MWh during summer and winter respectively, which is explained by the important role of gas in the Italian market.

Evaluating the effects of the nuclear moratorium in Germany in March of 2011, Thoenes (2014) develops a semiparametric cointegration model that incorporates daily prices of carbon emission allowances, natural gas, and electricity. Day-ahead electricity prices are used to calibrate the model, and future prices before and after the moratorium decision are analyzed to quantify the direct impact of the reduced available capacity and the increase in the gas and carbon emission allowance prices. The results indicate that the change of the gas and carbon emission allowances price is insufficient to explain the increase in the futures electricity prices. Immediately after the decision, futures electricity prices showed a capacity effect of 6 GW, but after several trading days, this effect decreased, which might be attributed to adaption effects, e.g., different exchange flows.

Instead of applying a classical linear regression model, Paraschiv et al. (2014) take a different approach by developing a dynamic fundamental model, which is used to analyze the impact of fuel and carbon prices as well as wind and photovoltaics on the day-ahead electricity price in Germany. By using separate time-varying coefficients for each hour of the day, they show how the impact of the fundamental variables depends on the load profile. For example, the effect of wind is highly dynamic, in hours at night with a low demand the impact of wind can lead to drastic price changes, and even negative prices might occur. Regarding the fuel prices, the investigation states that the coal price has a strong effect in hours with a typically higher demand, e.g., 12 and 18, where coal-fired power plants are often submitting the price-setting bid, and the influence of the gas price is strongest in peak-demand hours as gas-fired power plants usually have higher marginal costs than coal-fired units. However, due to the growing electricity production of photovoltaics, the effect of the gas price decreased over time. Furthermore, they find that the impact of the carbon emissions allowances price is higher in low demand hours, which is related to the fact that coal or lignite-fueled power plants produce more CO_2 emissions than gas-fired power plants.

In summary, the literature review shows the broad range of different approaches that are used to analyze the price impact of especially renewable energy sources. As the sharp price decline in wholesale prices from 2011 to 2015 is not sufficiently analyzed in the existing literature, this study enhances the literature by focusing on this extraordinary development of the German wholesale electricity prices in this study. However, as many other European electricity markets face the same price decline triggered more or less by the same drivers, the analysis can be transferred to other spot markets going through similar changes like the switch to renewable energies.

Whereas other studies apply a single method, which has its specific limitations, different modeling approaches are applied to the same research question to derive robust results taking into account these limitations. Moreover, robust results are provided by comparing two different years, thus, the stochastic influences e.g. a stronger or weaker wind year should have less importance. Contrary to other approaches, e.g. Kallabis et al. (2016), the agent-based model applied in this study is able to incorporate, for example, different market players, ramping costs and strategic behavior.

4.2 Modeling approach

In order to analyze the price development in the German electricity market, a threefold approach featuring a standard linear regression, a dynamic regression, and an agent-based simulation model is adopted and described in the following subsections (for an overview see Table 4.2). In this way, the results of the models applying the same data can directly be compared, and the strength and weaknesses of each approach can be considered. A linear regression model, for example, relies on strict assumptions such as the homogeneity of variance or the absence of multicollinearity in the input data that cannot always be ensured (e.g., Berry and Feldman, 1985). Additionally, non-linear dynamic effects, for instance the shutdown of several nuclear power plants in 2011 in Germany, are challenging to implement. In contrast to linear regression models, agent-based models can integrate these effects, but rely on detailed data that is not always publicly available—e.g., the efficiency of power plants or the local heat demand that companies often treat as trade secrets—and hence assumptions have to be made that are difficult if not impossible to verify.

4.2.1 Linear regression model

A multivariate regression model similar to O'Mahoney and Denny (2013) is used, where the hourly day-ahead electricity price p_t is the dependent variable and the explanatory variables consist of the hourly load $load_t$, the hourly forecasted feed-in from photovoltaics $solarForecast_t$ and wind $windForecast_t$ and the lagged daily prices for natural gas $gasPrice_{t-24}$, hard coal $coalPrice_{t-24}$ and CO_2 emission allowances $carbonPrice_{t-24}$.[4] Seasonal dummies ds_t are introduced to reflect systematic changes in the demand and the planned non-availability of power plants, which usually is

[4] Similar to Würzburg et al. (2013), it is found that the electricity exchange with neighboring countries was most often insignificant and alternated between having a positive or negative impact. This is probably related to the fact that the exchange flows strongly depend on the expected price differences with neighboring markets and as these differences are not included in the model, it is challenging to interpret the exchange flows in itself. Thus, the exchange is excluded from the regression.

Table 4.2 | Characteristics of the applied models. The input data required for the models increases from linear to agent-based models, as well as the complexity and the effort required for their maintenance. As a result, they are primarily suitable for different applications.

	Objective	Strength	Weakness
Linear regression model	Explain dependent variable (electricity price) through regressors, e.g., demand, wind	Easy to implement, wide-spread method	Multi-correlations have to be ruled out (Belsley et al., 1980), non-linear dynamic effects cannot be captured, e.g., the shutdown of several nuclear power plants
Dynamic fundamental model	Capturing the varying influence of fundamental parameters on dependent variable	Dynamic influences can be considered while keeping a closed mathematical structure	Estimation of coefficients is complex, the system of equations requires many parameters (Bai et al., 2013)
Agent-based model	Detailed bottom-up model of relevant system, e.g., power plants, market players	Imperfect markets and private information can be included, scenarios	Time-consuming implementation, decision-making rules hard to validate

higher during the summer and, hence, affects the fuel mix. Instead of choosing dummies to capture the daily and weekly patterns in the electricity prices that are caused by the different typical demand curves, which, e.g., are lower at night and on weekends, the regression was applied for each combination of the day type, either a working day or a non-working day $t \mapsto d \in \{WD, WE\}$, and the hour of the day $t \mapsto h \in \{1, 2, \ldots, 24\}$:

Table 4.3 | Test for multicollinearity for the 12 hour on working days. According to Belsley et al. (1980), it is most important to first focus on the highest condition number (condIdx), which shows moderate values and, thus, further analysis is of interest. In a next step, the corresponding variance-decomposition proportions need to be analyzed.

condIdx	intercept	load	wind	pv	gas	coal	carbon	dum1	dum2	dum3
1.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2.52	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.21	0.04	0.05
2.63	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.15
3.83	0.00	0.00	0.63	0.01	0.00	0.00	0.00	0.14	0.01	0.00
5.12	0.00	0.00	0.14	0.10	0.00	0.01	0.05	0.24	0.05	0.06
6.85	0.00	0.00	0.03	0.11	0.01	0.00	0.07	0.24	0.39	0.39
9.30	0.00	0.00	0.02	0.37	0.02	0.00	0.25	0.03	0.24	0.22
22.98	0.02	0.05	0.12	0.23	0.07	0.39	0.04	0.00	0.08	0.06
32.17	0.01	0.02	0.00	0.01	*0.88*	*0.60*	*0.59*	0.01	0.01	0.03
83.45	*0.97*	*0.93*	0.04	0.15	0.02	0.00	0.00	0.13	0.01	0.04

$$
\begin{aligned}
p_t = {} & \beta^0_{h,d} + \beta^{load}_{h,d} Load_t + \beta^{wind}_{h,d} windForecast_t + \beta^{solar}_{h,d} solarForecast_t \\
& + \beta^{gas}_{h,d} gasPrice_{t-24} + \beta^{coal}_{h,d} coalPrice_{t-24} + \beta^{carbon}_{h,d} carbonPrice_{t-24} \\
& + \textstyle\sum_{i=1}^{3} \beta^i_{h,d} ds_t + \epsilon_t \quad \text{if } d(t) = d \ \wedge \ h(t) = h
\end{aligned}
\tag{4.1}
$$

As the estimation of the β-factors can be affected negatively by multicollinearity, ideally, all exogenous variables should be uncorrelated. Although for some of the exogenous variables no relationship is expected, e.g., the emission allowances price and the wind feed-in, others might influence each other, for example, the fuel prices. In order to test for multicollinearity, a condition number test was carried out (Belsley et al., 1980). The test results do not indicate severe multicollinearity, but there is a strong relationship between the intercept and the load as well as a moderate dependency between the emission allowances, coal and gas price (Table 4.3).

Table 4.4 | Statistical outliers in the German day-ahead electricity prices. The number of statistical outliers in the period from 2011 to 2015 is comparatively low and averages only 0.35 %. Furthermore, it can be noted that more than half of the statistical outliers occur in 2012. *Source:* EPEX SPOT (2018b).

	prices < −25 EUR/MWh		prices > 100 EUR/MWh	
	occurrences	percentage	occurrences	percentage
2011	3	0.03 %	11	0.13 %
2012	23	0.26 %	60	0.68 %
2013	15	0.17 %	17	0.19 %
2014	16	0.18 %	0	0.00 %
2015	8	0.09 %	0	0.00 %

Outlier

The electricity prices from 2011 to 2015 contain only few outliers (see Table 4.4). However, these outliers, the upper as well as the lower ones, can significantly affect the results of the regression. Although outliers can contain valuable information and do not necessarily have a negative effect on the reliability of the results (Belsley et al., 1980), in this case the coefficient of determination R^2 improved considerably if the outliers were excluded from the calculation of the coefficients. In order to identify the outliers, the iterative process proposed by Trück et al. (2007) is applied. In a first step, all outliers are determined as prices that are outside of the interval $I = [-3\sigma + \tilde{x}, \tilde{x} + 3\sigma]$ where σ denotes the variance and $\tilde{x}$ the median of the electricity prices. This step is then repeated until all prices lie within the interval I.

4.2.2 Dynamic fundamental model

Similar to Paraschiv et al. (2014) and Karakatsani and Bunn (2008), a state space model with time-varying regression coefficients for the day-ahead electricity prices is developed. Applying an approach with time-varying coefficients is based on the assumption that the price formation is continuously adapting to the changing fundamental factors, e.g., sudden decommission of nuclear capacities, European market integration, new regulatory policies (e.g., market stability reserve) or new market rules (e.g., negative prices or block bids). Using a time-varying model has already proven to be effective in the studies of, e.g., Mount et al. (2006) or Karakatsani and Bunn (2010).

Similar to the linear regression model, the dynamic fundamental model is implemented for each hour of the day, so daily patterns, e.g., hours with high or low demand can be analyzed separately, yet in contrast, for this model only working days are included. This is related to the fact that coal, gas or carbon emission allowances are only traded on working days and thus for weekends/holidays no separate values exist which, however, are required for an adequate calibration.[5]

The incorporated variables differ slightly from the linear regression model with constant parameters. In order to deal with autocorrelation and include price signals, the lagged electricity price from the previous day for same hour of day is used. The lagged price should have a positive reinforcing influence on the current price, as extreme electricity prices tend occur within a short time frame (Huisman and Mahieu, 2003). The model is then formulated as follows:

$$y_{i,t} = X_{i,t}\, b_{i,t} + \epsilon_{i,t} \tag{4.2}$$

[5] For the linear regression model, the fuel price on weekends/holidays equals the last available traded price as the model does not take into account the price difference from the previous day. However, this approach is not applicable to the time-varying regression model that relies on the changes between time steps.

$$b_{i,t} = b_{i,t-1} + \eta_{i,t} \tag{4.3}$$

where for $i \in \{1, \ldots, 24\}$

$$\begin{aligned}
b_{i,t} &= \left(b_{i,t}^{0}, b_{i,t}^{load}, b_{i,t}^{wind}, b_{i,t}^{solar}, b_{i,t}^{gas}, b_{i,t}^{coal}, b_{i,t}^{carbon}, b_{i,t}^{exchange}, b_{i,t}^{meanlag-1}\right)' \\
X_{i,t} &= \left(x_{i,t}^{0}, x_{i,t}^{load}, x_{i,t}^{wind}, x_{i,t}^{solar}, x_{i,t}^{gas}, x_{i,t}^{coal}, x_{i,t}^{carbon}, x_{i,t}^{exchange}, x_{i,t}^{meanlag-1}\right) \\
\eta_{i,t} &\sim \mathcal{N}\left(0, Q_i\right) \\
\epsilon_{i,t} &\sim \mathcal{N}\left(0, R_i\right) \\
E\left(\epsilon_{i,t}\eta_{i,t}\right) &= 0 \\
Q_i &= \operatorname{diag}\left(\sigma_{i,0}^2, \ldots, \sigma_{i,meanlag-1}^2\right)
\end{aligned}$$

Equation (4.3) is called the transition equation and describes the change of the regression coefficients over time. Equation (4.2) represents the measurement equation, which relates the vector of the exogenous variables $X_{i,t}$ to the electricity price $y_{i,t}$. For the calibration of the model, first, the covariance matrices Q_i and R_i, which are assumed to be constant over time, are calculated with the maximum likelihood estimation. Afterward, the coefficients $b_{i,t-1}$ of the different fundamental factors are estimated with the Kalman Filter. This is done for each step t taking into account only the information that is already available at that time. Subsequently, for each hour of the day, the dynamic influence of the regarded factors can be analyzed.

4.2.3 Agent-based simulation model

In addition to the previously described regression models, an agent-based bottom-up model of the German electricity market is chosen. Agent-based models have already served as a tool to assess a wide range of research questions in the context of electricity markets (Guerci et al., 2010; Ringler et al., 2016; Weidlich and Veit, 2008). Depending on the scope, each model features a specific architecture, e.g., included market areas, timely resolution, and a different set of agents. These sets usually contain agents that represent the most relevant market participants who interact with other agents, who make their own decisions based on public and private information and learn from their past behavior (Tesfatsion, 2006). One major advantage of the agent-based approach is that imperfect markets such as oligopolies can be represented.

As reliable input data is essential for obtaining accurate results—especially for a bottom-up model that requires vast amounts of information—data needs to be chosen with care. For the model, all power plants of capacity larger than 10 MW are included with their techno-economic characteristics—i.e., efficiency, net capacity, fuel—based on an official list provided by the BNetzA (2016d). As national grid restrictions do not influence the day-ahead price formation in Germany, the German market area is regarded as a "copper plate."

In this model, the day-ahead market is operated by a central agent who receives bids from the different demand and supply agents. The supply side is modeled with a high level of detail. In order to determine the bids for its plants, each electric supply agent follows a multistep process. First, the price of the next day is forecasted. Based on the forecasted prices as well as the techno-economic restrictions, such as the start-up time of the power plant, a possible operating schedule is determined. Then, the supply agents submit hourly bids that include the variable costs and, in case the power plant is not already running, linear distributed start-up costs. To avoid start-up costs, block bids with a price below the variable costs can be placed for a base-load power plant, e.g., in a situation with high wind feed-in where the unit is expected to be out of the market for several hours. Thus, negative prices can be simulated as well. Different renewable energy sources, e.g., photovoltaics, wind, biomass, running water, are incorporated in the model. Based on hourly profiles, bids for each renewable technology are submitted by the grid operator. As the model focuses on the German electricity market, the exchange with other countries is represented by an exchange agent that trades the historical exchange volumes.

After all agents have submitted their bids, the market operator determines the market-clearing price and the accepted volume for all bids. The electric supply agents then determine the dispatch off their power plants for the next day and learn from their profits.

A more thorough description of the model as well as validation of the model's results is provided by Bublitz et al. (2014a).

4.3 Data and model validation

In this section, an overview of the different data sources and a descriptive analysis of the price drivers in the regarded period from 2011 to 2015 is provided. Subsequently, this information is used to validate the different selected models.

4.3.1 Data sources

As the day-ahead market price can be seen as an hourly reference price for the German electricity market, the German/Austrian day-ahead market price at EPEX SPOT was chosen for the analysis in the next section. Whereas the intraday market could have been chosen as well, in comparison the total trading volumes on the day-ahead market are several times higher. In order to adequately model the day-ahead price, all other data should represent the day-ahead level of information as more recent information was not available to the market participants when submitting their bids to the EPEX SPOT.

The hourly German electricity load $Load_t^*$ is published by the European Network of Transmission System Operators for Electricity (ENTSO-E, 2016). As the total monthly load values do not cover the total monthly consumption, e.g., 95 % for 2014 and 97 % for 2015[6], a constant for each month and year $c_{y,m}$ is added to the hourly load values

[6] This difference is mainly caused by the decentralized electricity generation and consumption in the grids of larger municipal utilities or industrial companies (BMWi, 2013).

so that 100 % of the consumption is represented.[7]

$$Load_t = Load_t^* + c_{m,y} \tag{4.4}$$

Due to the stochastic nature of the electricity generation from solar and wind, market participants do not have knowledge of the exact next-day electricity feed-in from solar and wind when participating in the day-ahead market and need to rely on forecasted values. Although each market participant uses undisclosed forecasts methods, there exists a publicly available forecast from each transmission system operators for their network area. Even though the data is usually published around 6 p.m. on the previous day and thus usually not available to the market participants when submitting their bids to the day-ahead auction, which takes place at 12 a.m, it is assumed that this forecast is a reliable approximation of the different forecasts of the market participants. As the forecasted feed-in differs from the total yearly feed-in published by the BMWi (2016c), the forecast is scaled by a parameter c_y:

$$Wind_t = c_y \cdot Wind_t^* \tag{4.5}$$

Due to the time-consuming transport, coal is not traded on the spot but derivatives market at the EEX. For the analysis in the next section, the monthly futures of the coal reference index API 2 at the ARA inland ports (API2-CIF-ARA-Coal-Month-Future) are used.

Since October 2011, there are two market areas for the trading of natural gas in Germany, GASPOOL that spans from North to East Germany and NetConnect Germany (NCG) from South to West Germany. For both market areas, a daily reference price is published at the EEX. The arithmetical average of these reference prices is then used for the case study.

[7] Although a linear scaling factor could also be applied, in some cases this results in unreasonably high load values, thus, adding a monthly constant is the better option.

Table 4.5 | Overview of the main input data. The data shows opposing trends. On the one hand, the feed-in from photovoltaics and wind is rising. On the other hand, the average load and the coal price are decreasing. Futhermore, the development of the carbon and natural gas price, is more volatile and shows no clear trend. *Source:* EEX (2016); ENTSO-E (2016).

		Load [GW]	PV [GW]	Wind [GW]	Gas price [EUR/MWh]	Coal price [EUR/MWh]	Carbon price [EUR/EUA]
2011	Mean	**62.13**	**2.24**	**5.56**	**22.78**	**12.48**	**12.97**
	SD	11.15	3.31	4.67	1.42	0.42	2.88
	Min	35.96	0.00	0.29	15.27	11.67	6.50
	Max	88.48	13.94	24.50	26.18	14.24	16.84
2012	Mean	**61.46**	**3.00**	**5.75**	**25.16**	**10.46**	**7.37**
	SD	11.12	4.53	4.57	2.07	0.62	0.71
	Min	35.98	0.00	0.25	20.24	9.41	5.71
	Max	87.03	20.64	24.46	40.25	12.34	9.31
2013	Mean	**60.57**	**3.54**	**5.89**	**27.16**	**8.84**	**4.48**
	SD	10.16	5.54	5.01	1.79	0.48	0.67
	Min	36.95	0.00	0.30	25.20	7.97	2.68
	Max	82.32	24.59	27.67	39.48	9.84	6.53
2014	Mean	**60.43**	**3.99**	**6.37**	**21.13**	**8.09**	**5.95**
	SD	10.67	6.03	5.55	3.01	0.30	0.70
	Min	36.00	0.00	0.30	15.36	7.53	4.35
	Max	83.03	25.61	29.72	28.28	8.93	7.24
2015	Mean	**59.50**	**4.39**	**10.01**	**19.88**	**7.21**	**7.67**
	SD	10.74	6.68	8.31	2.04	0.57	0.58
	Min	35.26	0.00	0.55	13.40	6.00	6.42
	Max	81.57	27.84	43.45	24.24	8.23	8.65

For the carbon price, the settlement price of the European Emission Allowances (EUA) of the relevant trading phase (II or III) at the EEX is applied. As no price exists for a weekend day or holiday, in this case, the last available price is extrapolated.

4.3.2 Descriptive analysis of the price drivers

An overview of the yearly averages, the standard deviation, the minimum and maximum for each of the selected fundamental variables is provided in Table 4.5. Several conflicting trends can be identified: From 2011 to 2015 the load and the coal prices are decreasing, whereas the feed-in from photovoltaics and wind is increasing. The gas price shows a more volatile development, first the price rises until 2013 and afterward drops to a lower level than in 2011. By contrast, the price of emission allowances falls until 2013 and then increases but stays behind the average value of 2011. The yearly standard deviation as well as the range of the emission allowances, hard coal, and natural gas price are relatively low in comparison to the load and the feed-in from wind and photovoltaics.

As OTC transactions only account for a minor volume of the short-term electricity trades, the day-ahead price for the German-Austrian market area can be regarded as a reference price. Electricity producers offer their conventional capacities based on their variable costs that mainly consists of fuel, emission allowances and operation and maintenance costs. Figure 4.2 shows these capacities sorted ascending by their variable costs (merit order curve) for the years 2011 and 2015. Base-load power plants, i.e., nuclear and lignite-fired power plants have the lowest variable costs, followed by coal and gas-fired power plants and peak load oil-fired units. The shut-down of roughly 11 GW of nuclear capacities in 2011 shifted the whole curve to the left, which alters the electricity price in most hours, as the minimum load from 2011 to 2015 is roughly 35 GW (see Table 4.5). This effect is partially compensated by the growing feed-in from wind and photovoltaics that increased from 2011 to 2015 on average by 6.6 GW. Moreover, the low carbon and coal price lead to increased competitiveness of coal-fired power plants. As the gas price has only slightly decreased and gas-fired fuel plants are not as strongly affected by the lower carbon price, gas-fired power plants – even those with a high efficiency – cannot compete with coal-fired power plants in 2015.

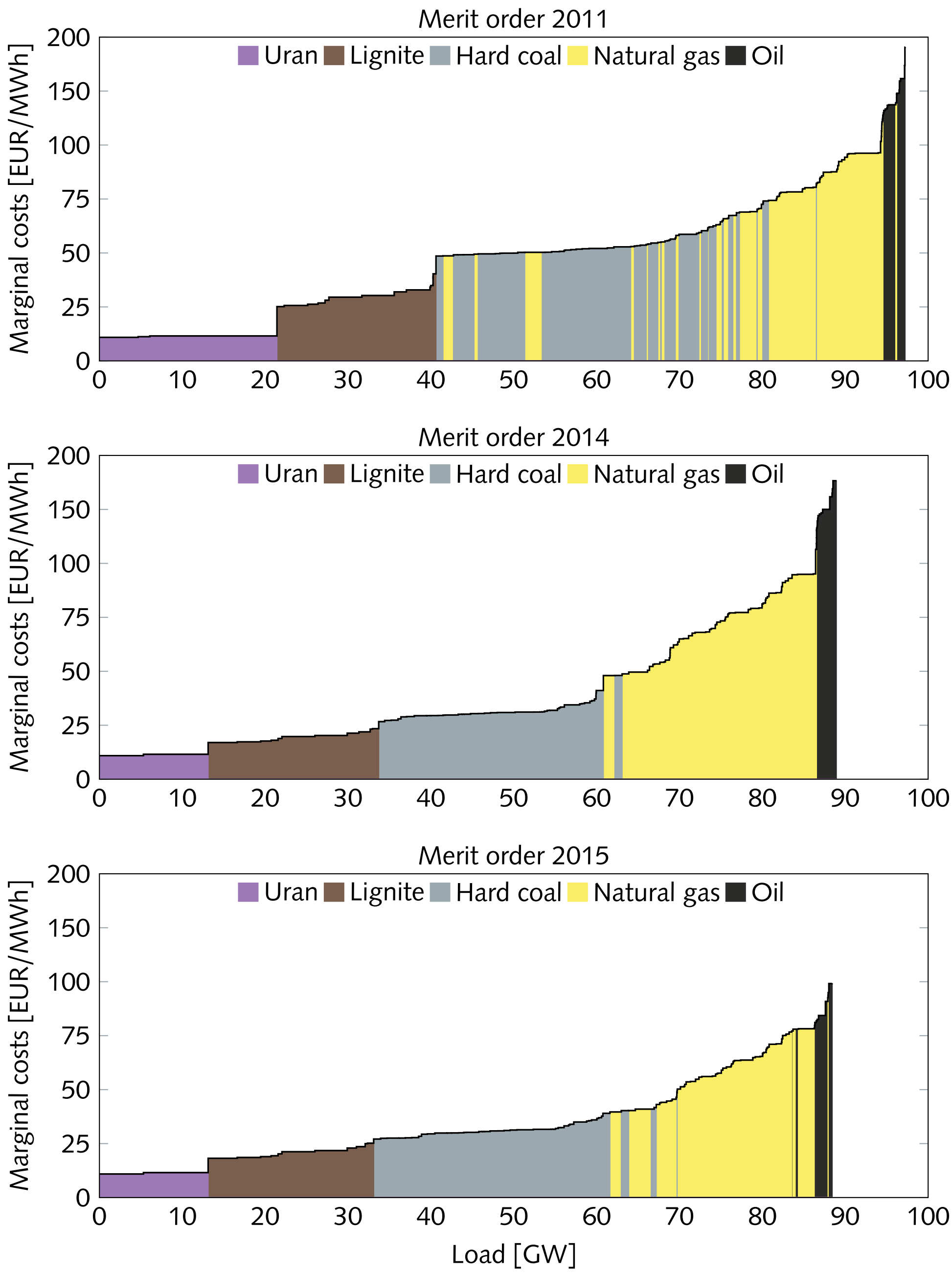

Figure 4.2 | The merit order of the conventional capacities in Germany. When examining the different merit orders, two aspects stand out. First, the total capacity has been severely reduced as a result of the nuclear phase-out. Second, the marginal costs, especially for coal and gas-fired power plants, are sharply lower. *Sources:* EEX (2016); BNetzA (2016d).

Figure 4.3 shows the relationship between the residual load[8] and electricity prices. It can be observed that an increase of the load usually results in a higher market price. If the residual load falls below a certain level and base-load power plants for some hours are forced to be turned off, negative prices can occur due to slow ramping rates, start-up costs and the obligation to provide system services such as the provision of primary reserve capacity. Negative prices strongly depend on the number of operational base-load plants and mostly occur at night, when a low demand coincides with a high feed-in from wind.

4.3.3 Model validation

In the following, a brief overview of the adequacy of the selected models for the price analysis described in the next section is given. Whereas the linear regression model and the agent-based model yield valid results, the results of the dynamic fundamental model are only of limited informative value.

The linear regression model has a high explanatory power with R^2 ranging from 0.69 to 0.83 (see Table 7.6). Also, as shown in Bublitz et al. (2014a, 2015a,b); Keles et al. (2016a), the agent-based simulation model is well capable of representing electricity market dynamics. Seasonal, weekly and daily patterns are adequately represented, which results in significant statistical figures, e.g., a R^2 above 0.75 or a mean absolute error (MAE) below 4.

However, the results of the dynamic fundamental model are of limited benefit for this analysis, even though the statistical figures show that the model possesses a high explanatory power (see Table 4.6). Although highly volatile factors such as the wind feed-in or load are adequately captured within the model, the coefficients of less volatile price drivers are insignificant most of the time or if significant, possess values that are non-plausible from a fundamental economic perspective. In contrast

[8] Here the residual load is defined as the load subtracted by the electricity generation from wind and photovoltaics.

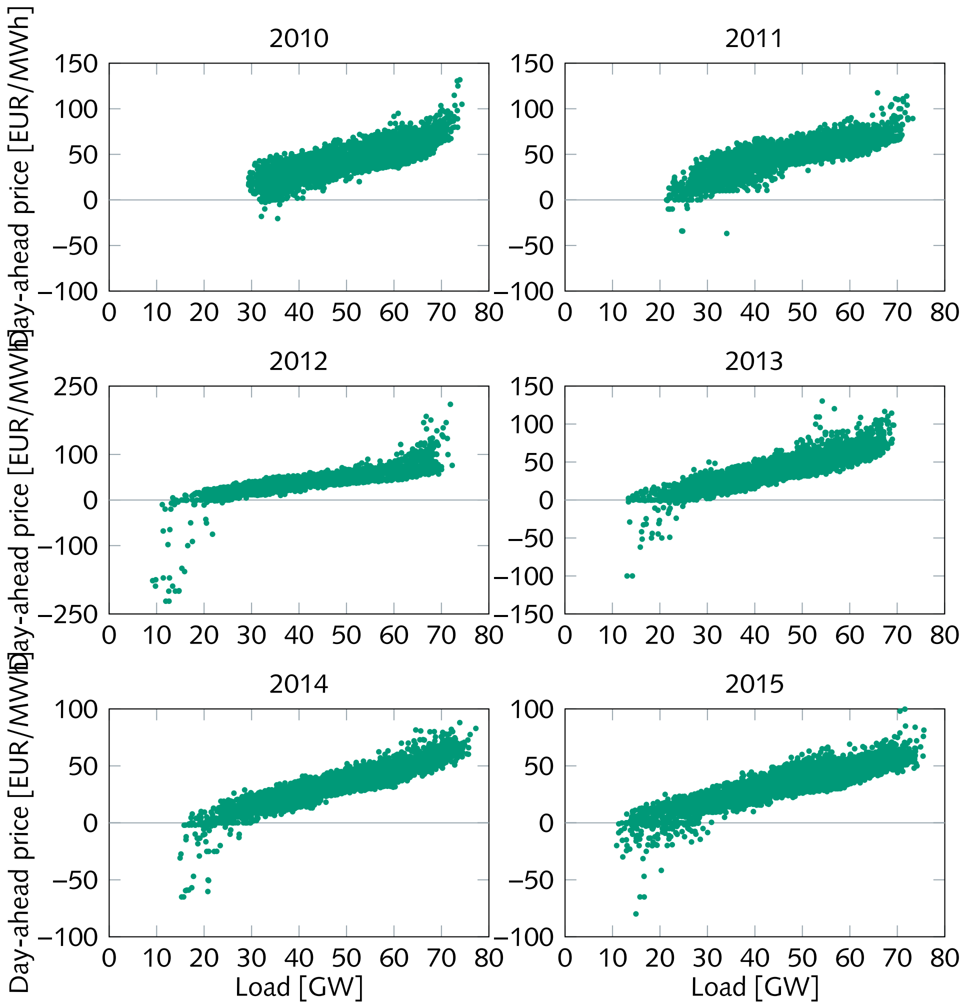

Figure 4.3 | The hourly day-ahead prices in the market area Germany/Austria as a function of the residual load for the years 2010–2015. The scatter diagrams for each year are similar to the corresponding annual merit order curves. Although in extreme situations, either with a very low or a very high residual load, the different values deviate more strongly from each other. Negative electricity prices usually occur incase the residual load drops below 30 GW. However, this is influenced by the availability and flexibility of the base load power plants as well as the duration of a low-load period. If maintenance work is carried out on many power plants at the same time, the limit from which negative prices occur can be lower. For example, in 2015, despite a residual load of less than 14 GW, there were no negative prices in certain hours. *Sources:* EEX (2018a); ENTSO-E (2016).

to the other obtained results, the dynamic model states that, e.g., an increasing coal price lowers the electricity price in peak hours by a factor of about 2. This is related to the fact that the calibration of the model is based on daily changes. However, a gradual development, e.g., the decline of the coal price that extends over several years, has an almost negligible short-term effect in comparison with the changes of the wind or photovoltaic feed-in. Strong daily changes or price shocks which could improve the results, only occur once in the regarded period, when the gas price increases from about 24 to 40 EUR/MWh within a few days. Besides this single significant change, there are no remarkable changes in the fuel prices in the short term. Therefore, the dynamic model cannot determine plausible beta coefficients for the long-term developing fuel prices. This approach can determine short-term effects quite well but indeed fails for the analysis of the mid- and long-term effect, which is at the focal point of this study. Hence, the linear regression model and the agent-based model are used in the following to analyze the rather long-term price development between 2011 and 2015.

4.4 Analysis of the price decline

In this section, an analysis of the decline of the German wholesale electricity prices based on historical data is carried out. First, the models from Section 4.2 are applied, then the price effect of the different fundamental factors is calculated and compared to existing studies. Then, it is shown how the development of the electricity price is affected by the selected fundamental factors in two scenarios.

Table 4.6 | Results of the linear regression and the dynamic fundamental model. Although both models have similar explanatory power, the values as well as the significance of the fundamental factors differ greatly and, as in the case of coal, even show a sign change for the 3 and 18 hour of the day.

Hour	3		12		18	
Model	Dynamic	Linear	Dynamic	Linear	Dynamic[a]	Linear
Observations	1247	1250	1247	1258	1222	1227
R^2	0.77	0.71	0.88	0.83	0.79	0.71
Adjusted R^2	0.77	0.71	0.88	0.83	0.79	0.71
MAE	3.17	3.75	3.63	4.38	5.30	5.49
MAPE	0.91	1.05	0.09	0.11	0.09	0.10
MAPE*[b]	0.17	0.18	0.09	0.11	0.09	0.10
RMSE	5.19	5.08	4.82	5.57	7.63	7.07
prob $b_{i,t}^{carbon}$	0.11	0.00	0.19	0.00	0.45	0.00
prob $b_{i,t}^{coal}$	0.15	0.04	0.73	0.00	0.01	0.00
prob $b_{i,t}^{gas}$	0.47	0.00	0.92	0.00	0.93	0.00
avg $b_{i,t}^{carbon}$	–0.14	1.16	0.77	1.11	0.78	0.84
avg $b_{i,t}^{coal}$	–0.78	0.25	0.20	0.93	–2.37	0.94
avg $b_{i,t}^{gas}$	0.13	0.22	0.59	0.62	1.02	1.08

[a] The first 25 values are not included for the calibration with the dynamic model as they contain a price jump, which strongly distorts the statistical figures, e.g., resulting in a RMSE close to 100.

[b] Due to the large impact of prices close to zero on the MAPE, all historical prices in the interval [-1, 1] are filtered for the calculation of the MAPE*.

4.4.1 Impact of each price driver

Based on the data mentioned above and the different modeling approaches introduced in Section 4.2, the main drivers for the electricity price development at the EPEX SPOT market is analyzed, especially the price reduction between 2011 and 2015. Therefore, the price reduction effect itself weighted with the hourly load in the analyzed year will be determined. The relative price effect will be calculated with the help of the regression model as well as with the agent-based simulation model. In the case of the regression model, the coefficients of the analyzed fundamental drivers will be used to determine the effect:

$$pe(x, T) = \frac{\sum_{t \in T} \beta^{x}_{d(t),h(t)} \cdot x_t \cdot Load_t}{\sum_{t \in T} Load_t} \tag{4.6}$$

In the case of the simulation model, two different runs are carried out. The first run is done by using the historical numbers of the analyzed fundamental parameter, e.g., carbon prices, and year, the second run is carried out by fixing the value of the analyzed parameter at the level of 2011, whereas the others remain the same as in the first run. The difference of electricity prices from both runs represents then the price (reduction) effect *pe* of the analyzed parameter:

$$pe(x, T) = \frac{\sum_{t \in T} \left(p^{x}_{t} - p^{ref}_{t}\right) \cdot Load_t}{\sum_{t \in T} Load_t} \tag{4.7}$$

Based on the models' results and the defined measures for the price reduction effect, the impact of main price drivers is analyzed in the following. Surprisingly, the price impact of the strong expansion of photovoltaics (from 2011 to 2015) in the last four years is not as strong as mentioned in recent public discussions (in total 2.1 EUR/MWh calculated with the agent-based model between 2011 and 2015 and 2.4 EUR/MWh with the regression model respectively). The impact of wind power, however, seems to be

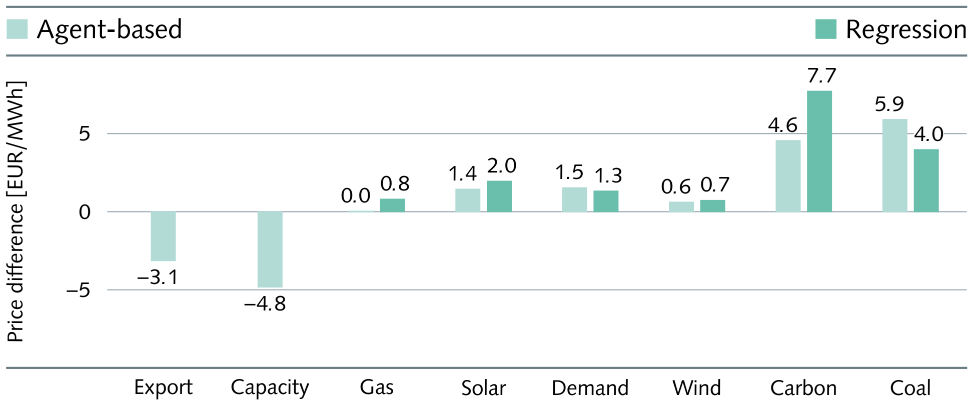

Figure 4.4 | Price effect in 2014. The effects in the year 2014 can be divided into three groups. The first group, consisting of export and capacity, has negative effects. This is followed by a group with a slight positive influence consisting of gas, solar, demand and wind. At the end comes a group with carbon and coal which shows a significant positive effect.

stronger, especially if the year 2015 is examined. The strong increase in German wind installations (on- and offshore) in 2015 combined with a windy year leads to a more significant wind merit-order effect. The price reduction resulting from wind power feed-in increased from 2014 to 2015. Whereas in 2014 values were below 1 EUR/MWh, in 2015, the agent-based and the regression model calculated values of 3.3 EUR/MWh and 4.4 EUR/MWh respectively. Both models determined a significant wind effect, which is, however, still below the price reduction effect of carbon or coal prices.

As illustrated in Figures 4.4 and 4.5, the decrease of coal and carbon prices has by far contributed the strongest to the price reduction between 2011 and 2014 or 2015. The regression model calculates a stronger price impact for the coal price than the agent-based simulation, whereas for carbon prices it is vice versa. However, both models determine these two parameters as the main price reducers with a total price reduction effect of almost 11 EUR/MWh.

The results of the agent-based model also show that the price reduction between 2011 and 2015 would be even stronger if there were the same amount of capacities in the market as in 2011. The decrease of power plant capacities in the German electricity

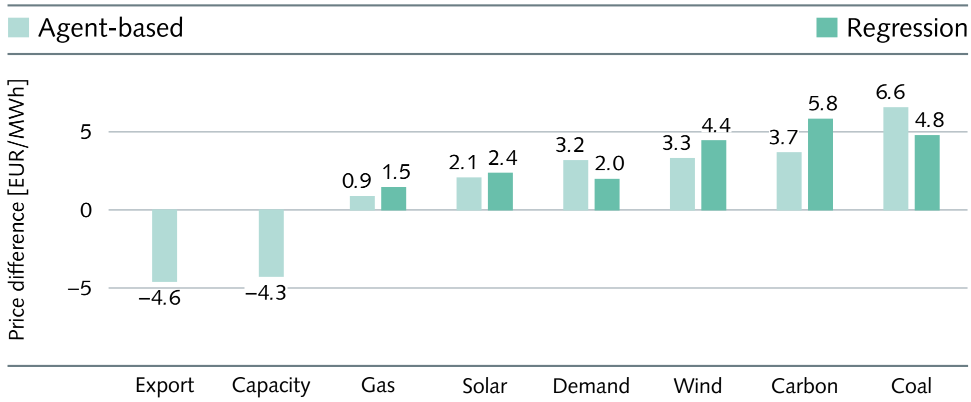

Figure 4.5 | Price effect in 2015. As in 2014, different groups can be identified. While the first group consists of export and capacity and has a negative effect, the division into further groups is no longer as distinct. For example, carbon and coal exhibit the strongest effect, but wind and demand also have a significant influence, whereas gas and solar have a weaker effect.

market (primarily due to the nuclear phase-out) and the growing net electricity exports lead to a recovery of prices by about 4.30 EUR/MWh and 4.60 EUR/MWh respectively.

However, there are some differences in the height of the impact of especially coal and carbon prices determined by the two different models (agent-based and linear regression model). Compared to the linear regression model, a lower price reduction effect of carbon prices is determined applying the fundamental agent-based approach. This may result from the fact that mainly lignite-fueled power plants, as the most carbon-intensive technology, show a corresponding change in variable costs, but as base-load power plants, they are rarely price setting. Additionally, the increase in the electricity price induced by the carbon price is lowered when a fuel switch, e.g., from coal to gas occurs. These effects are better captured by a fundamental agent-based model than by a statistical approach, so that price impact is much lower than the one in the case of the linear regression model. Another explanation of the strong effect of the regression model might be that it does not include other explanatory variables, e.g., the electricity flows with neighboring countries or the German plant fleet, which may have lead to an overestimation of the betas of the included variables.

In comparison with the regression model, the price effect of coal prices determined with the agent-based model is about 2 EUR/MWh higher. As the agent-based model incorporates each power plant with its technical characteristics, it has the strength to adequately represent changes in the merit-order and hence can provide a reasonable estimation of the induced price effect. The agent-based model, therefore, can also deal with non-linear relationships between coal and electricity prices, although the linear regression model cannot capture these non-linearities and may underestimate the price reduction effects caused by strong changes in coal prices.

Overall, it can be stated that both models determine the development of the coal and carbon emission certificate prices as the main source for the reduction of wholesale electricity prices the German electricity market faces since 2011, although the impact of the fluctuating renewables is considerably lower. However, the differences in the renewables effects between 2014 and 2015 show that this effect is growing especially with the ongoing expansion of wind capacity.

4.4.2 Scenarios for the price effect and economic feasibility of gas-fired power plants in 2020

In the following, the agent-based and the regression model are used to forecast the electricity prices in 2020 applying two scenarios for the fuel prices and a scenario for renewable power production extracted from P3 Energy & Storage (2015). For the "low" fuel and carbon price scenario, the fuel prices are assumed to remain at the current level, whereas the 2011 prices are assumed as a "high" price scenario for 2020. The results indicate that the volume weighted average prices in 2020 will fall to or even below 30 EUR/MWh, if the fuel and carbon prices stay on today's level. The additional reduction is expected to originate from the renewable power expansion until 2020, as all the other parameters remain on the same level as in 2015. An even stronger decrease would be expected without the already planned decommissioning of power plant capacity, which is considered in the agent-based model. This may also be the reason why the model predicts a smaller price reduction.

In contrast to the “low” price scenario, a strong increase in electricity prices is determined by both models in the “high” fuel and carbon price scenario, in which the electricity prices are expected to reach the 40 EUR/MWh level again. In this scenario, the fuel and carbon price increase to the level of 2011 would strongly overbalance the price reduction effect of the additional renewable energy sources (RES) expansion in the electricity sector.

Based on the electricity price development described above, Table 4.7 shows the number of hours with a positive spread between the electricity prices and the variable costs of a CCGT power plant. It is obvious that the number of hours with a positive spread is further reduced in the “low” fuel and carbon price scenario, although there is a significant increase in the “high” price scenario. The numbers of positive spread increase again to more than 2300 and even to 2782 determined by the agent-based model for the high price scenario. The increase in time with positive spread leads to a positive annual return for an exemplary CCGT power plant with 55 % efficiency rate, an emission factor of 0.202 MWh_{th}, other variable costs of 2 EUR/MWh and operational fixed costs of 19 000 EUR/MW (Blesl et al., 2012). However, the annual return is only slightly positive, so that it can be stated that without reaching the level of 2011 for coal and carbon prices or without further decommissioning of coal and lignite capacities, it will be difficult for even very efficient CCGT plants to operate economically feasible. Hence, if carbon and fuel prices remain at the low level of 2015, another market mechanism will be required to keep this efficient and flexible gas capacity in the market, especially if it should serve as backup capacity for fluctuant renewables.

Table 4.7 | Simulated day-ahead market prices. Volume weighted day-ahead market price, hours with a positive clean spark spread (CSS) and annual return under different fuel scenarios of an exemplary CCGT power plant (efficiency 55 %).

Year [-]	Scenario [-]	Price [EUR/MWh]	Annual return of a CCGT [kEUR/MW]	# hours with positive CSS [h]
2011	Historical	51.96	39.68	5338
2014	Historical	34.35	−6.31	2076
2015	Historical	33.05	−3.65	1947
2020	Low Regression	28.26	−8.07	1380
2020	Low ABSM	30.02	−4.18	1547
2020	High Regression	40.29	1.58	2382
2020	High ABSM	40.07	2.77	2782

4.4.3 Comparison of the results with existing studies

To embed these results into the discussion about electricity price drivers, the results are compared to those in the literature. As most of the existing studies focus only on the merit order effect of renewables, a comparison based on this criterion is carried out. This comparison is extended to the comparison of other price drivers analyzing the relative effect of these parameters, as there is hardly any study analyzing exactly price decline between 2011 and 2015. That is why the relative effect is also calculated from the absolute values described in other studies about price drivers.

However, at first, the regression model is applied to determine the total effect of fluctuant renewable energy sources. The price reduction of renewables, i.e. the merit order effect, is equal to 8 EUR/MWh in total for 2011 and 9 EUR/MWh for 2012, which is in the range of the merit order effect determined by Sensfuß (2011), who applies an agent-based model of the German electricity market (see Figure 4.6).

In 2015, the merit order effect of the renewables available in total corresponded to 14.70 EUR/MWh. Cludius et al. (2014) determine a similar effect, whereby they use estimated values for the electricity prices in 2015. This shows that the hourly linear regression model introduced in Section 4.2.1 produces similar results for renewable effect compared to other models.

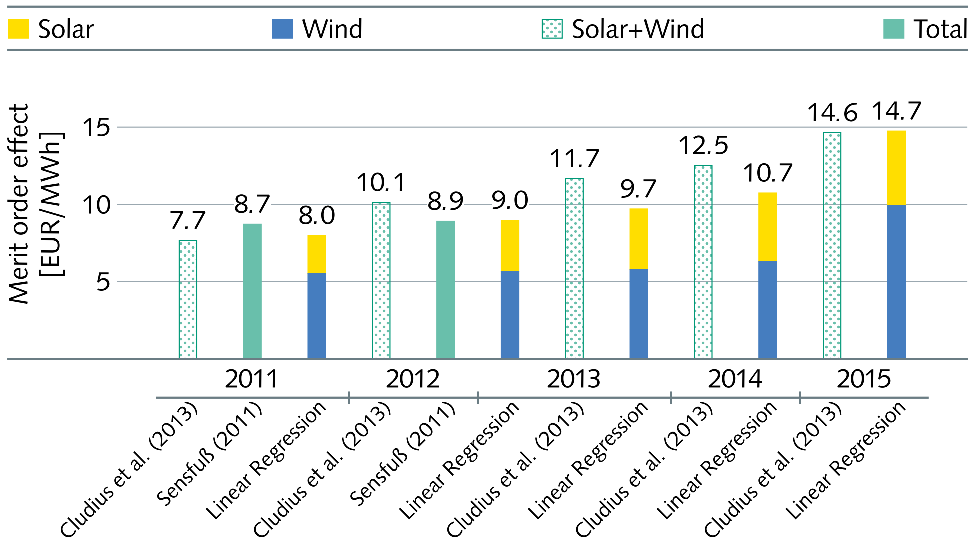

Figure 4.6 | Merit order effect in Germany from 2011–2015. The results from Cludius et al. (2014) for the period from 2013–2015 are taken the scenarios "reference" (2013/2014) and "high wind" (2015) and thus deviate from the historical feed-in values.

Comparing the results with Kallabis et al. (2016), who carry out a study for the decrease of German electricity future prices from 2007 until 2014, a similar relative price impact[9] can be observed for the prices of emission allowances. Kallabis et al. (2016) calculate an electricity price reduction of 0.72 EUR/MWh per EUR/EUA price reduction[10]. A relative price effect of 0.70 to 1.09 EUR/MWh EUR/EUA is determined. This also applies to the effect of renewables, which corresponds to a reduction of 0.13 EUR/MWh per TWh feed-in from RES and is close to the range of the effect of 0.08 to 0.12 EUR/MWh per TWh.[11] However, there are interdependent effects between the price of emission allowances and the level of renewable generation. While the

[9] Here, a relative effect means that the absolute effect is broken down to the marginal change of a price driver.

[10] Kallabis et al. (2016) show only the absolute effect in their study, but the relative effect can be derived via the base electricity futures with delivery in 2014 that were traded in Q4 2007 and Q4 2013.

[11] In a working version of the article, a value of 0.09 EUR/MWh was presented (Kallabis et al., 2015), closely matching the range in the results here.

effects are still investigated (Hintermann et al., 2016), in the long term, a demand reduction induced by an expansion of renewable energies should lower the carbon price. Nonetheless, for the regarded time period, renewables explain only a small part of the carbon price variations (Koch et al., 2014; Rickels et al., 2015). Also taking into account that the expansion of renewable energies in Germany has only a limited impact on the European level, the interdependent effects should be negligible for the results of this study.

Regarding the effect of coal and gas prices, the relative effect calculated from the absolute values of Kallabis et al. (2016) is not indicative due to the small total change of the price drivers within the analyzed period. However, within the time period of this study the fuel prices possess a significant development, thus, a strong price reduction effect for especially coal prices (0.91 to 1.12 EUR/MWh_{el} per EUR/MWh_{th}) could be determined. That is why the coal price beside the carbon price is determined as the most influencial price driver between 2011 and 2015, although they only see the carbon price as the primary driver of future electricity prices between 2007 and 2014.

4.4.4 Critical reflection of the modeling approach and results

Although the models described in Section 4.2 perform quite well to determine electricity price drivers, which becomes evident from the comparison of the results with other studies, the applied approaches have still room for improvement. To analyze the price impact of each influencing parameter between 2011 and 2015, two fundamentally different models are applied, a linear multiple regression model based on historical time-series of the prices and their drivers as well as a fundamental agent-based approach that considers all important system elements of the electricity market. Thereby, it has to be mentioned that especially the linear regression model is not able to capture the non-linearities in the price relation. However, as the different regression models are calibrated for each of hour of the day and a further differentiation for workdays and non-workdays is carried out, the models are applied to relatively similar situations in which the non-linearity should not severely distort the results.

The applied agent-based model simulates the German electricity system with its main fundamental elements. However, static import and export flows are used in the model to describe the electricity exchanges between Germany and its neighboring countries. This approach does not consider the reciprocal effect between prices and exports/imports and therefore possible changes in the price impact. In future research, this issue is to be addressed. However, no significant changes in the price effect of each price driver is expected, as wholesale prices in the neighboring countries show a similar development in the last years as the German electricity price and hence the cross-border flows are expected to be stable after varying a price parameter.

Additionally, the static approach used for the determination of the price effect needs to be addressed as well. More detailed, all other parameters are fixed at the level of 2015 and only the analyzed parameter between the values of 2011 and 2015 is changed. Thus, effects that a parameter would have on the other influencing parameters, if it stayed at the level of 2011, e.g., the lower availability of wind power would influence the exports are not regarded. As a smaller period of four to five years is regarded, in which no substantial differences in investments in power plants are expected, and the structure of the energy system may not severely change, the model error without considering the interdependencies is assumed to be rather low. Therefore, the calculated price reductions of each parameter are still meaningful. However, the analysis could be extended allowing more cross-dependencies in future with applying, e.g., vector autoregressive models.

4.5 Conclusions and policy Implications

In this study, the main price drivers for the electricity prices at the EPEX SPOT are analyzed focusing on their contribution to the price fall between 2011 and 2015 (decline of about 20 EUR/MWh). Although recent studies have mainly focused on the price effect of renewable energies, especially photovoltaics and wind, and determined the so-called merit order effect, in this chapter, the focus is set on the most important fundamental price drivers that lead to the price reduction in recent years. The results demonstrate that fuel and carbon prices still have a dominating impact on wholesale electricity prices and that the drop in coal and carbon prices was the main reason for the decline of electricity spot prices. Contrary to ongoing discussions, the strong expansion of photovoltaics in Germany was not the primary price driver, and the related merit-order effect was not primarily responsible for the sharp decline in wholesale electricity prices. The additional price effect of photovoltaics between 2011 and 2015 was relatively low compared to the effect of coal and carbon prices. Hence, the widespread opinion that the merit order effect of renewables is the main reason for the low prices faced today at wholesale markets has to be at least partly rejected. The total price effect of renewables since their market introduction makes up 14 to 15 EUR/MWh in Germany and is indeed a strong effect. However, the additional price effect between 2011 and 2015 is contributing only partly (5.40 EUR/MWh determined with the agent-based model, 6.80 EUR/MWh with the regression model) to the price decrease of almost 20 EUR/MWh in this period.

Using different types of models for this analysis proved to be helpful to gain a thorough understanding of the price impact of the regarded fundamental factors and to quantify the related uncertainty. As all models have their specific shortcomings, the application of several models helps to derive robust results. As the linear regression model can be implemented with relatively little effort, it seems to be a suitable way to identify the main trends. However, caution has to be paid for substantial input changes that might result in non-linear effects. In this case, the agent-based bottom-up model yielded more plausible results. Nevertheless, the implementation and application of this type of models are quite complex recent studies have mainly used regression models. The results of the time-varying regression model are of limited benefit for this analysis as in contrast to the volatile feed-in of wind and photovoltaics, the price effect of the gradually changing fuel and carbon prices is not adequately captured. The linear regression and the agent-based model, however, can also be used to analyze price effects in other countries and electricity markets, which faced a strong price decrease in the last years, too.

Furthermore, the price models are used to analyze the income situation and the annual return of gas power plants, which will still be required in the future energy system to balance fluctuating renewables. The scenario analysis for 2020 shows that if the coal and carbon prices recover to the level of 2011, a modern CCGT power plant can generate enough income to meet the variable and operational fixed costs. In this situation, the prices are high enough to achieve a slightly positive annual return. This may be sufficient to keep existing gas-based capacity in the market, but would not incentivize new investments. However, the development of other parameters, such as surplus capacities in the electricity market, plays also an essential role in the recovery of electricity prices and hence for the profitability of gas-fired power plants.

In this context, the decision of the European Commission to establish a market stability reserve from 2019 on and to take certificates out of the carbon market is a step towards the right direction. However, it may not be sufficient to completely remove the oversupply with certificates and thus, to achieve a recovery of certificate prices. Regarding the development of the current surplus volume in the next years, additional measures might be necessary to trigger an increase of carbon prices in order to make the operation of more environment-friendly gas power plants favorable compared to coal power plants. However, policy measures regarding carbon policy have to be installed at European level and should even be harmonized worldwide, as more restrictive national measures without harmonization can lead to "carbon leakage" or a new surplus of certificates in the EU-ETS market.

If carbon and coal prices remain at the current low level, the economic operation of gas power plants will be hardly possible, and it will be difficult for energy suppliers to keep them in the market. In this case, other market mechanisms, such as a capacity remuneration mechanism, will be required to operate these flexible power plants profitably and thus, to keep them in the electricity market. However, implementing new market regulations has to be done with care, as it can disturb the market operation resulting in new uncertainties for investors.

Continuing low prices will keep the market value of electricity generated from RES at a low level as well, which in turn makes higher funding volumes for renewables necessary. Also in this respect, the recovery of the prices of coal and emission allowances prices is essential.

Chapter 5

Insights from theory and real-world implementations of capacity remuneration mechanisms

A reliable electricity system remains one of the main objectives of energy market regulators. This objective requires the stimulation of adequate investments on the supply side by market prices, which are to be high enough to finance not only the operational but also the fixed costs. However, generating adequate price signals becomes more and more challenging during the energy transition phase mainly shaped by the expansion of distributed RES. This intensified the discussion on demand-supply adequacy and lead to the proposal and in some cases introduction of mechanisms to remunerate capacity providers. However, the necessity and the design of capacity remuneration mechanisms (CRMs) is diversely evaluated in the literature.

Due to the already large and still quickly growing number of studies on CRMs[1], it is increasingly hard to keep an up-to-date overview. As several real-world experiences in the implementation and administration of CRMs have been gained, reviews have already been carried out focusing on the practical lessons learned (e.g., Batlle and Rodilla, 2010; Beckers et al., 2012; Bhagwat et al., 2016b; Karacsonyi et al., 2006; Spees et al., 2013). However, due to the rapid development and frequent regulatory changes,

[1] In the literature, two other terms—capacity mechanism and capacity markets—are commonly used as synonyms for capacity remuneration mechanisms. Here, however, capacity markets have a narrower definition and are considered as a specific variant of the different mechanism to enumerate capacity (see Section 5.2).

some of the presented information is already obsolete. Other more broadly oriented studies provide a systematic description of CRMs as well as a descriptive comparison (e.g., DNV GL, 2014; Doorman et al., 2016; European Commission, 2016b; Hancher et al., 2015; Vries, 2007) or focus on the fundamental economic principles of CRMs, (e.g., Cramton et al., 2013; Stoft, 2002). Beside these studies on theoretical concepts of market design and CRMs as well as a review of mechanisms implemented in some countries, to the best knowledge of the authors, there does not exist a comprehensive review of the discussion and assessment of different design options for the electricity market in the literature.

Therefore, this chapter aims to guide both, new entrants and advanced researchers, through the field of electricity market design by providing a comprehensive and up-to-date overview of market design options. As the topic is well discussed in the literature and there are several real-world implementations of CRMs today, this chapter aims not only to review theoretical studies on electricity market design but also to describe a selection of real-world implementations of CRMs as alternative design options. This enables the potential reader to gain insights from theoretical approaches and related studies as well as from practical implementations.

In order to understand why there are so many approaches in theory and practice and how the discussion about the requirement for alternative design options evolved, Section 5.1 provides a review of the discussion about generation adequacy and about the performance of the energy-only market (EOM). Afterward, the focus is set on the assessment of market design options in the literature, both from a practical perspective and theoretical perspective. In the practical case, a selection of the most relevant design options implemented in electricity markets around the world is discussed (Section 5.2). The theoretical perspective considers the assessment of the impacts of different design options on regulatory targets, such as generation adequacy and RES integration (Section 5.3). The review of the latter perspective is carried out in focusing on the qualitative discussion of limitations and benefits of each market design option, as well as on the model-based analysis of impacts on different criteria, e.g., market welfare, security of supply or incentivizing flexibility. Finally, the main common findings are discussed, open questions with which researchers are currently confronted are pointed out, and a set of policy implications is derived (Section 5.4).

5.1 The ongoing debate about securing generation adequacy

The question of whether EOMs generate sufficient price signals to incentivize investments in generation capacity is closely linked to the specific characteristics of electricity markets, i.e., their long-standing barriers and more recent challenges. Therefore, after describing these characteristics, the discussion on generation adequacy is summarized to show the motivation behind CRMs, to make the review more comprehensive and to present the latest findings from the fast-growing literature in a broader context.

5.1.1 Existing barriers to generation adequacy

The barriers in the electricity sector can be clustered in physical and market-related ones. Physical barriers are mainly based on the fact that electricity systems need to balance generation and consumption in each node of the electricity grid at every point in time, as the disruption of electricity frequency can lead to severe damages, such as the destruction of connected devices or even the collapse of the entire power system (Kwoka and Madjarov, 2007). Usually, the most substantial amount of electricity is already traded several months or years in advance via forward contracts and OTC markets that allow energy suppliers to hedge their portfolio (Meeus et al., 2005). As the possibilities to store electricity economically are still limited, and deviations from the expected consumer demand as well as the unexpected unavailability of generation capacity induce a need for short-term trading, spot markets usually possess high liquidity. However, as a certain time between spot market clearing and fulfillment is still necessary to organize the delivery, current wholesale markets are unable to capture these temporal and spatial requirements in their clearing process. Hence, other market or regulatory mechanisms are required. Furthermore, due to the nature of the electricity network, a free-rider problem occurs as up to now the network cannot differentiate between customers with and without contracts guaranteeing a reliable supply (Lynch and Devine, 2017). Therefore, an EOM design without reliability contracts cannot discriminate between customers who are willing to pay for reliability and those who are not (Joskow and Tirole, 2007). These technical properties are one reason why electricity prices as the outcome of market equilibrium cannot carry all information and signals necessary for the reliable long-term operation and the required investments in the generation infrastructure.

One example for market-related barriers are price caps in spot markets, which are a regulatory barrier introduced to protect consumers and to avoid the abuse of market power in the absence of demand elasticity (Stoft, 2002). However, as Petitet et al. (2017) point out, price caps are usually set below the VoLL for political reasons, and the resulting investments in generation capacity are likely not sufficient to cover the electricity demand at all times. Even though it is theoretically possible to set shortage prices or price caps sufficiently high, i.e., equal to the VoLL, in practice its specific value would have to be determined first, a task often described as difficult or even impossible to perform (e.g., Cramton et al., 2013; Willis and Garrod, 1997).

Therefore, other measures may be required to replace signals coming from price spikes and to generate sufficient incentives for investments (Doorman et al., 2016). These additional measures are to be implemented to address the so-called missing money problem, which can be defined as the lost earnings beyond the price cap, especially for peak load power plants (see Figure 5.1b). More detailed, missing money is that part of these lost earnings that is necessary to cover the investment and all other fixed costs. For Joskow and Tirole (2007), missing money may also occur due to premature technical decisions of system operators to avoid market disequilibrium and brownouts[2]. Furthermore, Newbery (2016a) argues that even if earnings from price

[2] In the electricity system major failures result in brownouts or blackouts. A blackout is a disruption in a wider range of an electricity system up to a total collapse of the whole supply whereas a brownout

spikes are sufficient to cover fixed and capital costs, investors might not be willing to bear the associated risks and are unable to lay them off through futures and contract markets. In this case, the problem is referred to as missing market instead of missing money (Newbery, 1989).

Another problem in current wholesale electricity markets is that large parts of electricity demand are inelastic from a short-term perspective, e.g., households have a fixed rate for energy consumption in combination with a base rate tariff (Dütschke and Paetz, 2013) and, thus, do not actively participate in the volatile wholesale market or show any reaction even to drastic prices changes (Cramton and Stoft, 2005). Therefore, the marginal costs of base load and with increasing demand peak load power plants set the market price until the entire demand can no longer be met by the existing generation capacity (see Figure 5.1a). For this reason, Lynch and Devine (2017) state that the price signal for reliable supply and generation adequacy can be considered weak. Keppler (2017) even argues that many problems regarding security of supply could be solved if the demand side became more elastic and participated in the market efficiently. Furthermore, Aalami et al. (2010) claim that the implementation of demand response programs will lead to the reflection of wholesale prices in retail prices, especially, if new developments change the need for electric services and new business models are developed for the demand response measures. However, currently, the main burden of balancing the system to guarantee the reliable operation of the electricity grid in the short term and to ensure generation adequacy in the long term lies on the supply side.

implies an excessively reduced voltage that can result in equipment failure, e.g., overheating of electric motors (Blume, 2007).

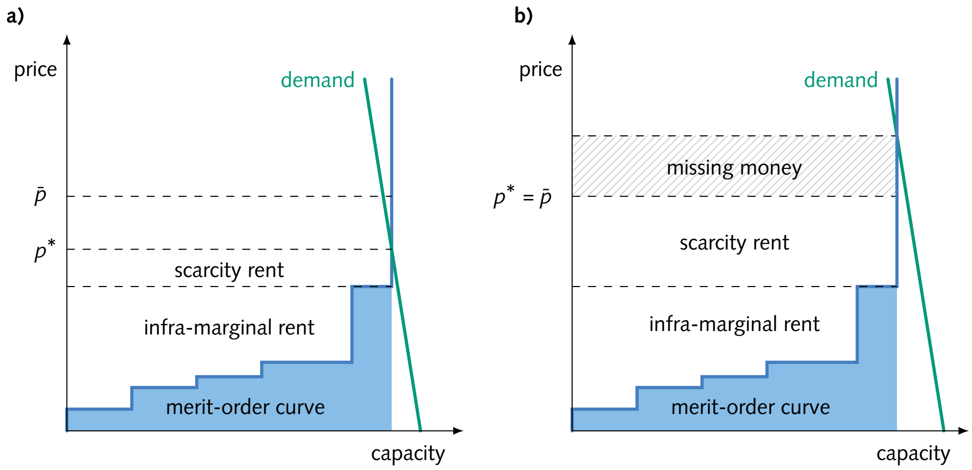

Figure 5.1 | Price setting in scarcity situations. a) The equilibrium price p^* is below the price cap $\bar{p}$ and an efficient outcome is achieved. b) The equilibrium price $p^*$is above the price cap $\bar{p}$, however, as the resulting price p^* is equal to the price cap, welfare losses occur (missing money).

5.1.2 Recently emerging challenges

In addition to the already mentioned long-standing barriers that exist on wholesale electricity markets, several recent developments revive the debate about mechanisms remunerating generation capacity, e.g., the rise of intermittent RES or the market-related and political uncertainties, such as the phase-out of specific technologies. The aim of the following paragraphs is, thus, to shed light on these developments.

Driven by the introduction of various subsidy programs, RES have experienced a remarkable rise[3].

Due to the dependence on weather conditions, the generation of photovoltaics (PV) and wind power is highly intermittent, and especially wind generation is hard to predict (Newbery, 2016b). As their level of electricity generation is semi-dispatchable, only a reduction is possible (Di Cosmo and Lynch, 2016; Lynch and Devine, 2017),

[3] The rise of RES is, for example, illustrated by the fact that between 2006 and 2016, the worldwide installed photovoltaic (PV) and wind power capacity grew by a compound annual rate of 48 % and 21 % to a worldwide installed capacity of 303 GW and 487 GW by the end of 2016 (REN21, 2017).

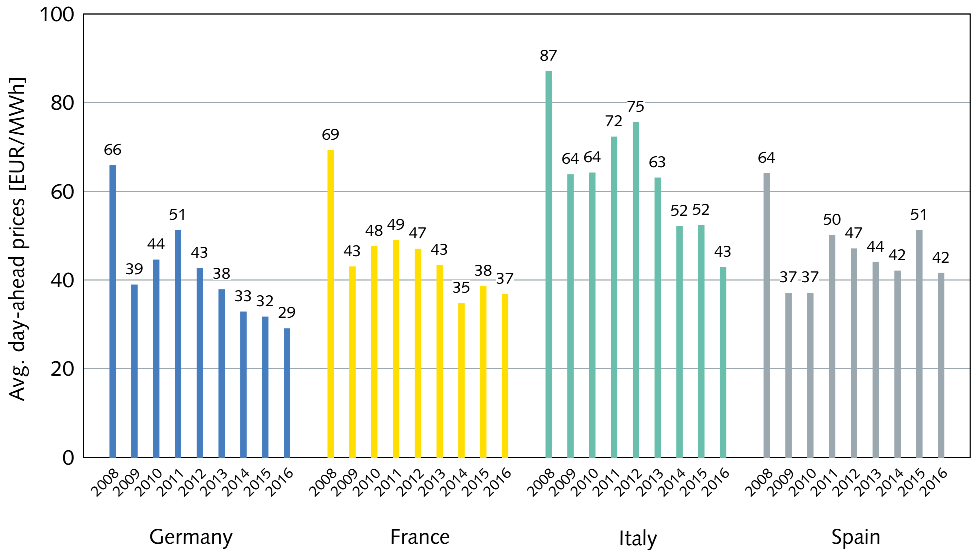

Figure 5.2 | The development of day-ahead prices in major European markets. In the last years prices show a clear downward trend, apart from the years 2009 and 2010, which can be regarded as outliers due to the impact of the global economic crisis. The comparison of the figures for 2008 and 2016 indicates a decline of about 50 % in Germany, France, and Italy, whereas the decline in Spain is about 33 %. *Sources:* ENTSO-E (2018b); EPEX SPOT (2018b); EEX (2017); OMIE (2017).

an additional need for flexibility is created, which, for example, can be provided by demand response measures, large-scale storage capacities or power plants with the ability to quickly ramp up or down (Cepeda and Finon, 2013; Pollitt and Anaya, 2016). Therefore, without further advancements, intermittent RES are currently unable to replace dispatchable conventional power plants adequately (Doorman et al., 2016; Hach et al., 2016) and the need for dispatchable generation capacity remains high. Moreover, as RES are often located away from the demand centers and the locations of capacities they replace, grid constraints will play a more pronounced role. RES are already mentioned as the main driver for grid congestions (Bruninx et al., 2013), and in the future, supply and demand need to be balanced at different geographical levels, e.g., at the local, the national or supranational level.

Finally, investors face different uncertainties regarding fuel and electricity prices and the regulatory framework, e.g., the nuclear phase-out decision, fossil fuel reduction or carbon emission targets. Even though the phase-outs affect supply security, Becker et al. (2016) claim that neither politicians nor scientists discuss lowering the level of security of supply to achieve a sustainable and affordable system. Beyond that, in case of an investment decision, the prompt commissioning of generation capacity—especially for controversial technologies (e.g., carbon capture and storage)—proves to be another obstacle, as the licensing process is tedious and adds another layer of uncertainty (Doorman et al., 2016).

5.1.3 The optimal functioning of energy-only markets and the necessity of capacity remuneration mechanisms

One, maybe the most persuasive, argument in favor of an EOM is that—even in the absence of an active demand response—resulting market prices are efficient and, thus, lead to sufficient long-term investments guaranteeing the least-cost long-term system if several key assumptions are met (Caramanis et al., 1982; Oren, 2005; Schweppe et al., 1988; Stoft, 2002): (1) the market is perfectly competitive, (2) market participants have rational expectations and (3) follow a risk-neutral strategy. However, in the light of the present state of electricity markets that feature several imperfections (Cepeda and Finon, 2011), these assumptions seem rather unrealistic, maybe even impossible to realize in practice. In real-world markets, a small number of producers often dominate the market, resulting in a duopoly or oligopoly (e.g., Schwenen, 2014), and invest strategically (Grimm and Zöttl, 2013; Zöttl, 2010). Furthermore, investors are usually rather risk-averse, i.e., building less capacity than risk-neutral investors would (Neuhoff and Vries, 2004). Moreover, market participants may not always have rational expectations, and in the presence of the large uncertainties, e.g., about the development of electricity prices, and the long lead times for new investments, electricity markets are prone to suffer investment cycles (Arango and Larsen, 2011; Ford, 2002; Olsina et al., 2006). The alternation between overcapacity and undercapacity results in inefficient market allocations, i.e., in the former case, unprofitable investments and, in the latter case, an excessive risk of load curtailment and high costs for consumers (RTE, 2014). Moreover, Vries and Hakvoort (2004) argue that even long-term contracts do not provide a solution as they offer consumers the opportunity to free-ride.[4] In addition, Keppler (2017) shows two other independent problems of an EOM. On the one hand, demand-side externalities in the form of transaction costs and incomplete information ensure that the social willingness-to-pay is greater than private willingness-to-pay for additional capacity. On the other hand, investments in generation capacities are not arbitrarily scalable, but rather take discrete values. In combination with dramatically lower revenues in the transition from underinvestment to overinvestment, investors have strong asymmetric incentives and, thus, tend to underinvest rather than to overinvest. Besides, Joskow and Tirole (2007) argue that scarcity rents are very sensitive to regulatory changes and that even minor mistakes are likely to have a significant impact on market prices.

Some of the more critical voices stress that market imperfections, especially the lack of demand response, will always persist in EOMs, and lead to the exercise of market power, which results in high price peaks. Thus, a different framework or additional measures, e.g., CRMs, are required to help to ensure generation adequacy efficiently (Cramton and Stoft, 2005; Joskow and Tirole, 2007). Others reply that the main problem of EOMs is the lack of political will to allow for unconstrained electricity prices[5] and periodic shortages (Besser et al., 2002; Hogan, 2005).

However, often it is argued that CRMs are inefficient and according to Oren (2000)

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[4] A problem with long-term contracts is that they are not contracted directly between consumers and utilities, but rather through load-serving entities as intermediaries. However, rational consumers prefer the cheapest retailer, which by avoiding long-term contracts does not contribute to the financing of peaking capacities.

[5] Although price caps are frequently mentioned as a source of the missing money problem, the data on market prices often tells a different story, e.g., since the establishment of the EEX in 2000, the upper price limit of the German spot market (3000 EUR/MWh) was not once hindering the price formation (EPEX SPOT, 2018b), the same seems to be the case in several US market areas from 2000 to 2006 (Joskow, 2008).

the least desirable instrument or according to Hogan (2017) only the third best option to ensure reliability, with the first option being the elimination of the leading underlying causes, e.g., incentivizing a flexible demand[6], and the second-best option being an administrative price curve for the usage of reserve energy. Wolak (2004) even claims that the rationale for CRMs is essentially a holdover from the regulated regime of the energy sector that encourages over-investment and is highly susceptible to market power, thus, frequently requiring regulatory intervention to set a non-distorted capacity price. In a recent publication, Wolak (2017) instead argues that generation adequacy can be ensured by establishing a market for standardized forward contracts and mandating retailers to participate in order to provide sufficient liquidity. He states that in this way generation adequacy can be ensured at the lowest possible cost, as scarcity is reflected in the forward prices and investors are provided with the necessary financing.

Summing up, whether the EOM is able to guarantee generation adequacy, is still discussed intensively in the literature. It is apparent that the efficient allocation of resources by an EOM is a highly challenging task, given the particular combination of the unusual characteristics of the electricity market. Here, the utilization of real-world experience to draw general conclusions is of limited use. In case, some analysts argue that the developments on a particular market serve as an example for the inherent shortcomings of an EOM, advocates respond that the market has not been able to function well due to regulatory mistakes (Doorman et al., 2016). Beyond that, Hogan (2017) states that the financial distress present in many European as well as North American electricity markets, can be attributed to overcapacities. Nonetheless, recent developments have raised serious doubts on the effectiveness of an EOM so that many politicians deem the introduction of CRMs necessary.

[6] In the future, if end consumers start to participate directly in the market via smart meters, they could specify in detail what price they are willing to pay for each consumption level. If the price is too high, the smart meter will switch off individual consumers directly, for example, the washing machine, while leaving others connected, e.g., the lights and refrigerator. Thereby, the missing money problem could be avoided (Newbery, 2016a).

5.2 Market design options and current status of real-world implementations

In order to highlight the practical relevance of the market design concepts developed in the literature, an overview of several CRMs currently implemented or in the planning stage around the world is provided in the following. These real-world implementations are classified with respect to some key characteristics. Then, conclusions and implications for future implementations are presented. Thereby, this section provides a helpful backdrop for a deeper understanding of the literature reviewed in Section 5.3.

5.2.1 Generic types of capacity remuneration mechanisms

Typically, CRMs are designed to incentivize investments and thus improve generation adequacy, i.e., avoid shortage situations. This is implemented by offering capacity providers income on top of the earnings from selling electricity on the market (Hawker et al., 2017). Yet, the mechanisms vary in the way the required quantities that are supplied and the corresponding capacity prices are determined (Hach et al., 2016).

The European Commission (2016b) distinguishes between volume-based mechanisms, where a specific capacity sufficient to guarantee the desired level of generation adequacy is set and then results in a market-driven price, and price-based mechanisms, where the amount of the procured capacity is steered by setting a target price. Both categories can also be subdivided into market-wide and targeted approaches. Whereas market-wide mechanisms provide support to all capacity in the market, targeted mechanisms aim at supporting only a subset, e.g., newly built capacity or capacity expected to be required additionally to the one already provided by the market. More specifically, six different types of mechanisms can be differentiated (for typical characteristics, see Table 5.1):

(1) Tender for new capacity. Financial support is granted to capacity providers in or-

Table 5.1 | Typical characteristics for different types of CRMs. Whereas the typical characteristics are shown here, due to specific requirements, the actual specifications may sometimes vary, e.g., a strategic reserve can also be procured bilaterally. *Sources:* European Commission (2016b); Hancher et al. (2015); Neuhoff et al. (2016, 2013).

Type	Category	Procurement/ Market type	Participation in other markets	Product	Main regulatory parameters
Tender for new capacity	volume-based/ targeted	centralized/ auction	yes	firm capacity	capacity volume
Strategic reserve	volume-based/ targeted	centralized/ auction	no	reserve capacity	capacity volume, activation rule, trigger event
Targeted capacity payment	price-based/ targeted	centralized/ auction	yes	firm capacity	capacity price, eligibility criteria
Central buyer	volume-based/ market-wide	centralized/ auction	yes	call option	capacity volume, strike price
De-central obligation	volume-based/ market-wide	decentralized/ bilateral	yes	reliability certificate	security margin, penalties
Market-wide capacity payment	price-based/ market-wide	centralized/ auction	yes	firm capacity	capacity price

der to establish the required additional capacity. Different variations are possible, e.g., financing the construction of new capacity or long-term power purchase agreements.

(2) Strategic reserve. A certain amount of additional capacity is contracted and held in reserve outside the EOM. The reserve capacity is only operated if specific conditions are met, e.g., a shortage of capacity in the spot market or a price settlement above a certain electricity price.

(3) Targeted capacity payment. A central body sets a fixed price paid only to eligible capacity, e.g., selected technology types or newly built capacity.

(4) Central buyer. The total amount of required capacity is set by a central body and procured through a central bidding process so that the market determines the price. Two common variants of the central buyer mechanism include the forward capacity market (Cramton and Stoft, 2005, 2006) and reliability options (Batlle et al., 2007; Pérez-Arriaga, 1999; Vázquez et al., 2001).

(5) De-central obligation. An obligation is placed on load-serving entities to individually secure the total capacity they need to meet their consumers' demand. In contrast to the central buyer model, there is no central bidding process. Instead, individual contracts between electricity suppliers and capacity providers are negotiated.

(6) Market-wide capacity payment. Based on estimates of the level of capacity payments needed to bring forward the required capacity, a capacity price is determined centrally, which is then paid to all capacity providers in the market.

5.2.2 Current status of implementation around the world

While the first CRMs in the US date back to the 1990s, European countries only rather recently started implementing such mechanisms or are currently evaluating tailored solutions. However, the European trend towards applying CRMs stands in contrast to the European Commission's preference for the EOM as an approach to trigger new investments and provide signals for decommissioning in case of overcapacities (Petitet et al., 2017). Some further countries outside of Europe and the US, such as

Australia and Colombia, are also relying on CRMs in order to guarantee generation adequacy.

An overview of several real-world implementations of CRMs as well as planned mechanisms is provided in Table 5.2 and Figure 5.3. The country-specific approaches differ not only with regard to the chosen type of the mechanism but also with regard to the respective administrators and the eligible technologies. Further characteristics of some currently active mechanisms can be found in Section 5.5.

The European Commission has already recognized the issue of cross-border effects and, thus, continuously assesses the conformity of planned and implemented mechanisms with EU State aid rules (for an overview of the cases see European Commission, 2017c). For a lawful public intervention in the market, the European Commission (2013) requires the respective member state to demonstrate the essential need for any capacity remuneration. Moreover, any mechanism must ensure that distortions of competition are minimized and technology neutrality is guaranteed. The latter aspect includes the eligibility of demand-side measures or foreign generation capacity, which, for example, has led to several adjustments of the French decentralized capacity market mechanism.

5.2.3 Discussion and implications for future implementations

An expert survey conducted by Bhagwat et al. (2016b) reveals that the CRMs implemented in the US have effectively—but likely not efficiently—contributed to reaching the different regions' respective reliability goals. For this reason, the experts generally advise the EU to rely on EOMs and not implement CRMs. If, however, CRMs are to be implemented in Europe, they recommend using consistent and transparent rules with minimum subsequent modifications. Moreover, based on the US experience, it seems advisable to base the capacity remuneration on the availability of the respective resources in actual scarcity conditions. Since these recommendations are quite generic,

Table 5.2 | Capacity remuneration mechanisms around the world. Several CRMs have already been established in the last years. Differences in the implementation of these mechanisms, particularly exist with regard to the technologies eligible for funding, such as intermittent renewable energies or interconnectors.

			Administrator		Eligible technologies			
Type	Country	Start	TSO	RA	TPP	VRES	DSM	IC
Strategic reserve	Belgium	2014	x	x	x		x	
	Germany[1]	2018[2]	x	x	x		x	
	Sweden	2003	x		x		x	
Central buyer	Colombia	2006		x	x	x		
	Ireland[3]	2017[2]	x	x	x	x	x	x
	Italy[3]	2018[2]	x	x	x		x	x
	Poland[4]	2018[2]	x	x	x	x	x	x
	UK	2014	x	x	x	x	x	x
	US – ISO-NE	1998	x		x	x	x	x
	US – MISO	2009	x		x	x	x	x
	US – NYISO	1999	x		x	x	x	x
	US – PJM	2007	x		x	x	x	x
De-central obligation	Australia – SWIS	2005	x	x	x	x	x	
	France	2015	x		x	x	x	x
	US – CAISO	2006	x	x	x	x	x	x
	US – SPP	2018	x		x	x	x	x
Targeted capacity payment	Spain[5]	2007	x		x			

Abbreviations: DSM—demand side management, IC—interconnector, RA—regulatory authority, TPP—thermal power plant, TSO—transmission system operator, VRES—variable renewable energy sources

[1] In Germany, two separate mechanisms have been discussed that can be classified as a strategic reserve. In 2016, a security stand-by arrangement for lignite-fired power plants with a total capacity of 2.7 GW was introduced in order to attain national climate targets. Furthermore, an additional so-called capacity reserve was supposed to be active in winter of 2018/19 to ensure generation adequacy, however, the planned schedule was not met.
[2] Year of planned implementation.
[3] To date, targeted capacity payments are used.
[4] Currently, a strategic reserve is implemented.
[5] This refers to the now in place "availability service" mechanism. An additional mechanism named "investment incentive" was abolished in 2016.

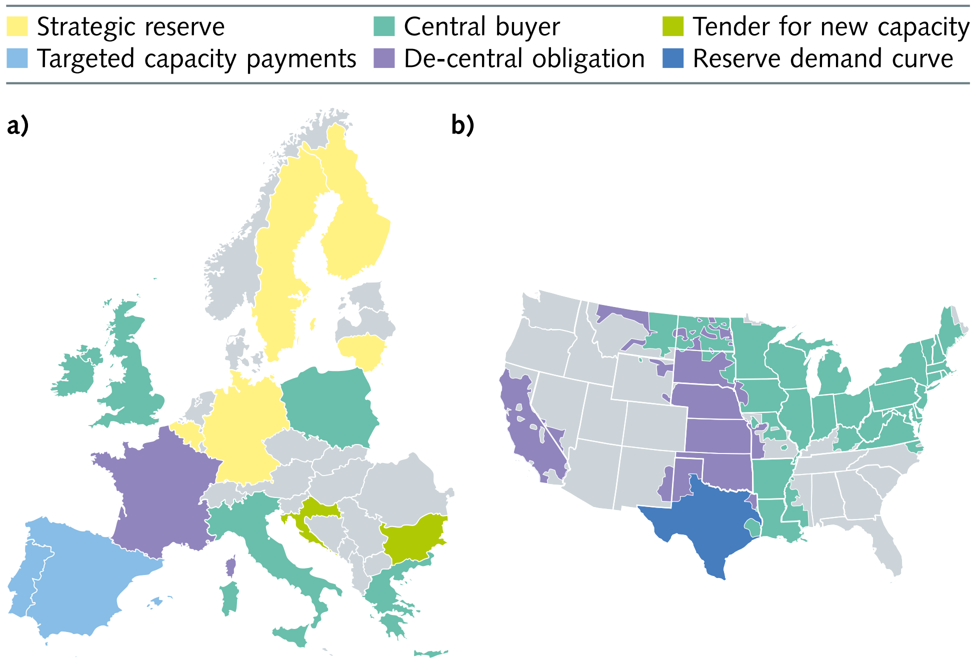

Figure 5.3 | Current and future implementation of CRMs in Europe and in the US. Overview of **a)** the future situation of CRMs in Europe when all planned mechanisms are implemented and **b)** the current situation in the US. The situation is more diverse in Europa due to uncoordinated national approaches and diverging interests. Whereas only two different types of CRMs are found in the US, a specific case is the Texas ERCOT market, where the EOM is supported by an artificial reserve demand curve that produces high price signals to incentivize investments or DSM. *Sources:* ACER and CEER (2017); Chow and Brant (2018); EirGrid plc and SONI Limited (2017); European Commission (2014b, 2016a,b); Hancher et al. (2015); Midcontinent Independent System Operator (2019); Roques et al. (2016); U.S. Government Accountability Office (2017).

they are also applicable to any country outside of Europe which is considering the implementation of a CRM.

Bhagwat et al. (2016b) further state that cross-border inefficiencies are currently not considered a major issue in the US, even though the introduction of the PJM mechanism has likely been a key driver for the subsequent implementation of a CRM in the neighboring MISO region. In this respect, the situation is different in Europe, where the European Commission (2011b) considers a single European electricity market—also termed "internal electricity market"—essential in order to ensure competitive, sustainable and secure energy supply in the future. This is contrasted by several European countries already using or currently implementing individual mechanisms to increase generation adequacy on a national level (see Section 5.2.2). Yet, in a highly interconnected electricity system like the European one, the uncoordinated implementation of local mechanisms might lead to numerous potentially adverse cross-border effects, which are described in detail in Section 5.3.6.

5.3 Findings on capacity remuneration mechanisms in the literature

After analyzing real-world implementations of CRMs, the findings in the literature are discussed below. In view of the large number of studies, the findings have been structured based on the specifically investigated topics. This allows to compare similar studies and to derive common results. In many of the analyses, e.g., for evaluating dynamic long-term effects—such as the occurrence of investment cycles—the use of models is highly suitable (Hary et al., 2016). Table 5.3 gives a quick overview of the existing approaches available in the literature including the regarded market characteristics or the considered research topics. For example, this allows determining which model type is particularly suitable for the assessment of specific research questions.

The summary of all the findings in the literature, including but not limited to the mentioned models in the table, is structured by the economic implications of CRMs in the following subsections. At first, the design elements of CRMs are briefly discussed. Then, it is examined how CRMs are affected by market power, risk aversion, and investment cycles. Subsequently, it is analyzed how CRMs influence market welfare and neighboring market areas. Finally, the impact of CRMs in an electricity market characterized by a higher share of RES and a more flexible demand side is evaluated.

Table 5.3 | Modeling approaches for capacity remuneration mechanisms. Summarized overview of modeling approaches regarding the development of electricity market design with a focus on capacity remuneration mechanisms.

Publication	Model type[a, b]	Model scope	Market area	Design criteria	Market power	Uncertainty	Investment cycl.	Efficiency	Cross-border	High RES	Flexible Res.	Research subject
Aalami et al. (2010)	analytical	interruptible technologies	Iran								x	impact of capacity market programs on the load level and shape
Abani et al. (2018)	system dynamics	spot market, decommissions (retirement of unprofitable existing genera-tion)/investments	hypo-thetical			x						impact of risk aversion on the performances of capacity remuneration mechanisms (competitive EOM, capacity market and strategic reserve) with investors facing an uncertain peak load
Abani et al. (2016)	system dynamics	spot market, decommissions (retirement of unprofitable existing genera-tion)/investments	hypo-thetical			x		x				impact of investors' risk aversion on investments in generation capacity in a competitive EOM and a capacity market
Assili et al. (2008)	system dynamics	electricity dispatch, investments	hypo-thetical				x					influence of capacity payments on market prices and the reserve margin
Bajo-Buenestado (2017)	analytical (perfect competition, subgame perfect Nash equilibrium)	spot market, investments	Texas (ERCOT)		x			x				welfare effects of introducing capacity payments in a competitive market and a market with dominant firms
Bhagwat and Vries (2013)	agent-based (EMLab)	spot market, investments, transmission constraints	Ger-many, Nether-lands				x					effect of a strategic reserve in Germany on investment behavior and leakage of reserve benefits to the Netherlands

Publication	Model type[a, b]	Model scope	Market area	Design criteria	Market power	Uncertainty	Investment cycl.	Efficiency	Cross-border	High RES	Flexible Res.	Research subject
Bhagwat et al. (2014)	agent-based (EMLab)	spot market, decommissions/investments, transmission constraints	hypothetical based on Germany						x			cross-border impact of a capacity market and a strategic reserve on consumer costs and on investments in the affected markets
Bhagwat et al. (2016a)	agent-based (EMLab)	spot market, decommissions (retirement of unprofitable existing generation)/investments, transmission constraints	hypothetical based on Germany		x	x	x					effectiveness strategic reserve in the presence of a high RES share
Bhagwat et al. (2017a)	agent-based (EMLab)	spot market, decommissions (retirement of unprofitable existing generation)/investments, transmission constraints	hypothetical based on Germany			x	x			x		effectiveness of a capacity market in the presence of imperfect information and uncertainty, declining demand shocks resulting in load loss, and a growing share of RES
Bhagwat et al. (2017b)	agent-based (EMLab)	spot market, decommissions (retirement of unprofitable existing generation)/investments	hypothetical based on the United Kingdom			x	x					effectiveness of a forward capacity market with long-term contracts in the presence of a growing share of RES
Bhagwat et al. (2017c)	agent-based (EMLab)	spot market, decommissions (retirement of unprofitable existing generation)/investments, transmission constraints	hypothetical based on Germany						x			cross-border effects of a capacity market and/or a strategic reserve

Publication	Model type[a, b]	Model scope	Market area	Design criteria	Market power	Uncertainty	Investment cycl.	Efficiency	Cross-border	High RES	Flexible Res.	Research subject
Briggs and Kleit (2013)	analytical (Ramsey optimum)	spot market, investments, transmission constraints	hypo-thetical		x			x				efficiency of capacity payments
Bublitz et al. (2015a)	agent-based (PowerACE)	spot market, decommissions (retirement of unprofitable existing genera-tion)/investments, operating reserve, transmission constraints	Germany		x			x				effects of the proposed strategic reserve in Germany on security of supply and costs
Cepeda and Finon (2011)	system dynamics	spot market, investments, transmission constraints	hypo-thetical			x	x					cross-border effects of an EOM (with/without price cap) and a forward capacity market
Cepeda and Finon (2013)	system dynamics	spot market, investments	hypo-thetical based on France							x	x	effects of large-scale deployment of wind power generation on spot prices and reliability of supply
Creti and Fabra (2007)	analytical (perfect competition, monopoly)	spot market, transmission constraints	hypo-thetical					x				firms' optimal behavior and market equilibrium in capacity markets with the possibility to sell to a foreign market under both perfect competition and monopoly
Ehrenmann and Smeers (2011)	stochastic equilibrium	electricty dispatch, investment	hypo-thetical		x	x						effects of risk (fuel prices, carbon market) on investment decisions in generation capacity

Publication	Model type[a, b]	Model scope	Market area	Design criteria	Market power	Uncertainty	Investment cycl.	Efficiency	Cross-border	High RES	Flexible Res.	Research subject
Fabra et al. (2011)	analytical (Nash equilibrium)	investments	hypo-thetical			x		x				effects of price caps and auction formats (uniform-price/discriminatory) on investments and the capacity ratio between two firms
Fan et al. (2012)	stochastic equilibrium	electricity dispatch, investments	hypo-thetical			x						effects of uncertainty and risk aversion on investments in high and low-carbon capacities
Franco et al. (2015)	system dynamics	electricity dispatch, decommissions (retirement of unprofitable existing genera-tion)/investments	Great Britain				x					effect of central buyer capacity market on investment cycles and long-term market stability
Genoese et al. (2012)	agent-based (PowerACE)	spot market, investments, operating reserve, transmission constraints	hypo-thetical based on Spain					x				impact of a capacity payment mechanism on the long-term development of investments in conventional capacities and on electricity prices
Gore et al. (2016)	single-firm optimization	spot market, transmission constraints	Finland, Russia					x	x			short-term effects of an EOM and an energy-plus-capacity market on cross-border trade and efficient allocation of transmission capacity
Grave et al. (2012)	single-firm optimization (DIME)	electricity dispatch, decommissions (based on age)/investments	Germany								x	development of security of supply under the increasing penetration of intermittent RES and the need for backup capacity and electricity imports

Publication	Model type[a, b]	Model scope	Market area	Design criteria	Market power	Uncertainty	Investment cycl.	Efficiency	Cross-border	High RES	Flexible Res.	Research subject
Grimm and Zöttl (2013)	analytical (perfect competition, Nash equilibrium)	spot market, investments	Germany					x				influence of spot market design on firms' investment decision for different regimes of spot market competition (competitive prices and Cournot-Nash equilibrium)
Hach et al. (2016)	single-firm optimization	spot market, decommissions (retirement of unprofitable existing genera- tion)/investments	Great Britain		x							affordability, reliability, and sustainability of a central buyer capacity market (for new or new/existing capacity)
Hach and Spinler (2016)	real options for single investor	spot market, investments	Europe	x		x						effect of capacity payments on investments in gas-fired power plants under rising renewable feed-in
Hary et al. (2016)	system dynamics	spot market, decommissions (retirement of unprofitable existing genera- tion)/investments	hypo- thetical			x	x	x				dynamic effects of a capacity market and a strategic reserve mechanism on investment cycles
Hasani-Marzooni and Hosseini (2013)	system dynamics	electricity generation, investments, operating reserve, transmission constraints	Iran				x	x				effect of a (regional) capacity payment mechanism and a price cap on investments in Iranian electricity market
Herrero et al. (2015)	single-firm optimization	electricity dispatch, investments	hypo- thetical	x								effects of the implemented pricing rule (linear and non-linear) on long-term investment incentives

Publication	Model type[a, b]	Model scope	Market area	Design criteria	Market power	Uncertainty	Investment cycl.	Efficiency	Cross-border	High RES	Flexible Res.	Research subject
Hobbs et al. (2007)	agent-based (single agent)	investments	hypo-thetical	x		x						effects of alternative demand curves in the PJM market on reserve margins, generator profitability, and consumer costs
Höschle et al. (2017)	analytical (Karush-Kuhn-Tucker)	electricity dispatch, investments, green certificates	Belgium					x				effect of central buyer capacity market and strategic reserve on the reserve margin and non-participating RES
Jaehnert and Doorman (2014)	single-firm optimization	electricity dispatch, investments, transmission constraints	Nether-lands, Germany							x		effect of a capacity mechanism or an increased price cap on generation capacity under rising renewable feed-in
Joskow (2008)	analytical (Ramsey optimum)	spot market, investments	hypo-thetical		x						x	sources of the missing money problem in imperfect markets
Joskow and Tirole (2007)	analytical (Ramsey optimum)	spot market, investments, operating reserve	hypo-thetical		x	x		x				efficiency of capacity obligations
Keles et al. (2016a)	agent-based (PowerACE)	spot market, decommissions (retirement of unprofitable existing genera-tion)/investments, operating reserve, transmission constraints	Germany					x				generation adequacy in different market designs (EOM, central buyer capacity market, strategic reserve)
Kim and Kim (2012)	single-firm optimization	electricity dispatch, investments, transmission constraints	South Korea					x				effects of zonal forward capacity markets on investments across market zones

Publication	Model type[a, b]	Model scope	Market area	Design criteria	Market power	Uncertainty	Investment cycl.	Efficiency	Cross-border	High RES	Flexible Res.	Research subject
Laleman and Albrecht (2016)	statistical	electricity dispatch	Belgium								x	occurrence of electricity shortages and surpluses in the presence of a high share of nuclear combined with a high share of intermittent RES
Lara-Arango et al. (2017a)	analytical (joint maxi-mization, Nash equilibrium, perfect competition) combined with scenario experiments	spot market, investments	hypo-thetical				x	x				economic welfare of a central buyer capacity market and a strategic reserve
Lara-Arango et al. (2017b)	agent-based	electricity dispatch, decommissions (based on age)/investments	hypo-thetical			x	x					influence of uncertainty on producer surplus and market stability in case of capacity payments and a capacity auction
Léautier (2016)	analytical (two-stage, Nash equilibrium)	spot market, investments	hypo-thetical		x	x		x				optimal investment in different market designs (financial reliability options, physical capacity certificates, single market for energy and operating reserves)
Le Coq et al. (2017)	analytical combined with scenario experiments	spot market, investments	hypo-thetical		x			x				relationship between prices, market power and investment under three different regulatory regimes (low price cap, high price cap, capacity market)

Publication	Model type[a, b]	Model scope	Market area	Design criteria	Market power	Uncertainty	Investment cycl.	Efficiency	Cross-border	High RES	Flexible Res.	Research subject
Levin and Botterud (2015)	single-firm optimization	electricity dispatch, investments, spinning-up and non-spinning reserve	Texas (ERCOT)							x		ability of three different market mechanisms (Operating Reserve Demand Curves, Fixed Reserve Scarcity Prices and fixed capacity payments) to provide generator revenue sufficiency and resource adequacy with increasing amounts of renewable energy
Lueken et al. (2016)	statistical	spot market	PJM	x		x						resource adequacy requirements in the PJM market area assuming plant failures are either independent or correlated
Lynch and Devine (2017)	analytical (Karush-Kuhn-Tucker)	spot market, decommissions (retirement based on higher maintenance costs)/investments, refurbishment	hypo-thetical					x				impact of refurbishment under capacity payments and reliability options
Maere d'Aertrycke et al. (2017)	stochastic equilibrium	electricity dispatch, investments	hypo-thetical			x		x				impact of incomplete risk trading (Contracts for Difference, Reliability Options with and without physical back-up) on investments
Mastropi-etro et al. (2016)	agent-based (two-stage)	spot market, investments	hypo-thetical	x								impact of penalty schemes for under-delivery on capacity mechanisms' effectiveness and unit reliability

Publication	Model type[a, b]	Model scope	Market area	Design criteria	Market power	Uncertainty	Investment cycl.	Efficiency	Cross-border	High RES	Flexible Res.	Research subject
Meunier (2013)	analytical	electricty dispatch, investment	hypo-thetical			x						effect of risk and risk-aversion on the long-term equilibrium technology mix
Meyer and Gore (2015)	analytical (Nash equilibrium)	spot market, investments	hypo-thetical		x			x	x			influence of competition and market power on market welfare of CRMs (strategic reserve and reliability options)
Milstein and Tishler (2012)	analytical (Nash equilibrium)	spot market, investments	Israel					x				the rationality of underinvestment if profit-seeking, non-abusive producers construct and operate either one—base or peaking—generation unit (or both)
Mohamed Haikel (2011)	analytical (three stage, Karush-Kuhn-Tucker, Nash equilibrium)	spot market, investments	hypo-thetical		x	x		x				comparison of three CRM (reliability options, forward capacity market, and capacity payments) in regard of efficiently assuring long-term capacity adequacy in Cournot oligopoly, collusion, and monopolistic situations
Neuhoff et al. (2016)	single-firm optimization	electricity dispatch, transmission constraints	hypo-thetical	x				x	x			benefits of coordinated cross-border strategic reserves
Ochoa and Gore (2015)	system dynamics	electricity dispatch, investments, transmission constraints	Finland, Russia					x	x			effects of maintaining a strategic reserve in Finland in combination with the different scenarios of interconnection expansion and trading arrangements with Russia

Publication	Model type[a, b]	Model scope	Market area	Design criteria	Market power	Uncertainty	Investment cycl.	Efficiency	Cross-border	High RES	Flexible Res.	Research subject
Osorio and van Ackere (2016)	system dynamics	electricity dispatch, investments, transmission constraints	Switzerland						x		x	impact of the nuclear phase-out and the increasing penetration of variable RES on security of supply
Ozdemir et al. (2013)	single-firm optimization (COMPETES)	electricity dispatch, decommissions (based on age)/investments, transmission constraints	Europe						x			cross-border effects (investments, electricity generation, market prices, and importexport flows) of a unilateral introduction of a German capacity market
Park et al. (2007)	system dynamics	spot market, investments	South Korea					x				effects of capacity incentive systems—loss of load probability or fixed capacity payments—on investment in the Korean electricity market
Petitet et al. (2017)	system dynamics (SIDES)	electricity dispatch, decommissions (retirement of unprofitable existing generation)/investments	hypothetical			x		x				effects of capacity mechanisms on security of supply objectives assuming risk-averse and risk-neutral investor behavior in power markets undergoing an energy transition
Ringler et al. (2017)	agent-based (PowerACE)	spot market, investments, operating reserve, transmission constraints	CWE Market area					x	x			effects of cross-border congestion management and capacity mechanisms on welfare and generation adequacy in Europe (potential development of the CWE Market)

Publication	Model type[a, b]	Model scope	Market area	Design criteria	Market power	Uncertainty	Investment cycl.	Efficiency	Cross-border	High RES	Flexible Res.	Research subject
Schwenen (2014)	analytical	spot market	hypo-thetical		x			x			x	effect of market structure (duopoly with symmetric and asymmetric firm size) on security of supply in a capacity market and an EOM
Schwenen (2015)	analytical	capacity auction	New York (ICAP)	x								strategic bidding to coordinate on an equilibrium in multi-unit auctions with capacity constrained bidders
See et al. (2016)	single-firm optimization	electricity dispatch, transmission constraints	hypo-thetical						x			reinforcing cross-border competition for the supply of capacity generation with the help of a flow-based forward capacity mechanism
Tashpula-tov (2015)	log-linear regression	spot market	England and Wales		x							effects of regulatory reforms on incentive and disincentive to exercise market power
Traber (2017)	analytical (Karush-Kuhn-Tucker)	spot market, decommissions (based on age)/investments/ retrofitting, transmission constraints	Ger-many, France, and Poland					x				effects of capacity remuneration mechanisms on welfare and distribution (consumers/producers) with a focus on conventional power plants
Vries and Heijnen (2008)	agent-based	spot market, decommissions (based on age)/investments, interruptible technologies	The Nether-lands		x	x	x					effectiveness of different market designs (an EOM with and without market power, capacity payment, operating reserves pricing, capacity market) under uncertainty about demand growth

Publication	Model type[a, b]	Model scope	Market area	Design criteria	Market power	Uncertainty	Investment cycl.	Efficiency	Cross-border	High RES	Flexible Res.	Research subject
Weiss et al. (2017)	hybrid (single-firm optimization/agent-based)	spot market, investments	Israel							x	x	market prices, reliability, and consumer costs in different market designs (EOM, capacity market, strategic reserve)
Willems and Morbee (2010)	analytical	spot market, investment	Germany			x		x				effects of an increasing number of derivatives on welfare and investment incentives in electricity market with risk averse firms
Winzer (2013)	agent-based	spot market, investments	Great Britain			x		x				robustness of various capacity mechanisms to welfare losses caused by regulatory errors

[a] Here, the column "Model scope" excludes all CRMs as these are mentioned in the column "Research subject."
[b] If only marginal costs are regarded to determine, which capacity is operating, the term "electricity dispatch" is used. However, the term "spot market" is used if the strategic behavior of market participants is explicitly modeled.

5.3.1 Generic design criteria for a capacity remuneration mechanism

The design of a CRM is a complex challenge where the ideal solution depends on the particular market conditions, e.g., the existing capacity mix and the demand characteristics (Batlle and Rodilla, 2010; Cepeda and Finon, 2011; Keppler, 2017; Spees et al., 2013). Here only the most important design parameters as well as selected parameters for specific mechanisms are discussed, for further criteria, e.g., see Ausubel and Cramton (2010); Batlle and Pérez-Arriaga (2008) for different design criteria, Herrero et al. (2015) for pricing rules, Neuhoff et al. (2016) for the design of a strategic reserve or Schwenen (2015) for the design of capacity auctions.

Target for system availability

Once the decision to introduce a CRM has been made, a system-wide target for system adequacy is often set, which helps to determine in the case of volume-based mechanisms the required capacity level or in the case of price-based mechanisms the targeted capacity price (Hogan, 2017). Here, the loss of load expectation (LOLE)[7] is frequently used and often a value of 1 day in 10 years is targeted (North American Electric Reliability Council [NERC], 2009), which however has been criticized as arbitrary and too strict to be economically optimal (Cramton and Stoft, 2006). Taking into account correlated outages among generators and the expected future demand, then the required quantity of demand to reach the target for system availability is derived.

Demand curve

In quantity-based CRMs, a demand curve—usually referred to as the variable resource requirement demand curve—must be defined that sets the price for each capacity level.[8] Although in theory, it makes sense to rely on the declining marginal value of capacity (Cramton and Stoft, 2007), in practice, due to the difficulty of estimating this value, usually, a linear curve based on an upper and a lower price limit is used (Spees et al., 2013). The upper price cap needs to be high enough to incentivize sufficient investments when the system is tight and typically equals a multiple of thenet cost of new entry (NetCONE)[9]. The lower price cap is usually set equal to zero and marks

[7] However, the LOLE is not free of criticism, for example, as it refers only to curtailment and does not indicate to what absolute or relative extent in relation to the market size the curtailment occurs. Here, the unserved energy (UE) metric provides more insight (Lueken et al., 2016). An overview of further reliability target can be found at Milligan et al. (2016).

[8] Instead of demand curves sometimes a fixed capacity is set. However, Hobbs et al. (2007) advise against this practice as sloped demand curves bear lower risks for consumers.

[9] Similar to the determination of the VoLL, the determination of the cost of new entry (CONE) or the NetCONE, which is usually carried out by the regulator, is also a controversial matter. The choice or the cost-basis of the reference technology, and, thus, its value is often adjusted over time (Cramton

the capacity level when the desired reserve margin is reached. However, sometimes, in order to avoid a total price collapse or prevent market manipulation from large purchasers of capacity, a higher price is set, e.g., 75 % of the NetCONE (Miller et al., 2012). When setting the upper and lower price limit, it also needs to be taken into account that a steep demand curve may lead to more volatile prices and, thus, greater uncertainty for investors (Bhagwat et al., 2017b).

Eligible technologies

In a next step, the definition of the capacity product needs to be established, and it has to be decided which capacity resources are eligible. Sisternes and Parsons (2016) argue that CRMs should be technology-neutral and allow for the participation of all elements that can reliably provide capacity (conventional and renewable generation, storage technologies, demand-side measures). If certain technologies were to be excluded, the mechanisms would introduce hidden subsidies for the technologies eligible for the CRM, which in turn would lead to higher costs for consumers. At the same time, however, it must be noted that this can possibly lead to conflicts regarding the reduction of carbon emissions, for example, in Great Britain highly emission-intensive diesel-fueled generators received capacity payments (S&P Global Platts, 2015). Moreover, Hach and Spinler (2016) propose to consider the specific policy targets and only consider a technology-neutral selection if generation adequacy is to be achieved at the lowest possible cost. However, if particularly flexible capacities are required or an ambitious emission reduction target needs to be achieved, this should be reflected in the selection of technologies. Although it is cheaper to only pay for new generation capacities, it must be noted that this strategy works only once as investors will adjust their behavior onwards and demand additional protection and risk premiums (Cramton et al., 2013).

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and Stoft, 2007, 2008; Jenkin et al., 2016). Regarding the related uncertainty, Spees et al. (2013) propose to better set a higher value to avoid unreliable outcomes.

Verification system

In order to enhance the performance of CRMs, a performance incentive system is required, which ensures that the capacities actually provide the contracted capacity when the system is tight (Mastropietro et al., 2016; Vázquez et al., 2002). This can either be implemented through a financial penalty for non-compliance (Cramton and Stoft, 2005) or by restricting the amount a resource can provide to its firm capacity (Batlle and Pérez-Arriaga, 2008). The experiences from the United States show that despite the existence of explicit penalties, underperformance has occurred, which underlines the importance of designing and implementing a performance incentive system (Mastropietro et al., 2017). If a financial penalty is chosen, it needs to be high enough to incite investors to compliance, which, however, increases the risk of investors and this is reflected in their bids. For the exact amount of the penalty, it is possible to rely on the VoLL, the capacity price or the NetCONE.

5.3.2 Potential and effects of market power

Central buyer mechanisms, e.g., reliability options, are able to lower the potential for market power in wholesale electricity markets (Le Coq et al., 2017; Léautier, 2016) and thereby improve the efficiency and reduce the total bill of generation, which is defined as the sum of the revenues realized by the electricity generators (Hach et al., 2016). By contrast, compared to an EOM, Bhagwat et al. (2016a) claim that a strategic reserve increases the possibility to exercise market power as the opportunities to withhold capacities, which can result in an activation of the reserve and extreme market prices, become more frequent compared to an EOM where market power is primarily exercised during capacity shortage hours.

In addition, as Mohamed Haikel (2011) points out, market power might be exerted when introducing non-market based mechanisms, e.g., capacity payments. However, the possible entry of a new competitor makes them less vulnerable to market power than, e.g., day-ahead markets, where in the short term no additional competition can emerge (Schwenen, 2014). Therefore, it seems unlikely that the additional potential of market power within a CRM will compensate for the lower potential in the wholesale markets. Nonetheless, Joskow (2008) advocates that the capacity price could be reduced by the quasi-rents earned by a hypothetical peaking unit, thereby disincentivizing the exercise of market power. Furthermore, Cramton and Stoft (2008) argue that only new investments could be allowed to set the capacity price to mitigate market power, existing capacity must either submit a zero bid or is not allowed to participate at all. The rationale behind this approach is that although established market players might possess market power, they are unable to exercise it if there is competitive new entry and only new investments set the price.

5.3.3 Influence of uncertainty and risk aversion

In the majority of the considered analyses, it is assumed for simplification purposes that all decision-makers act risk-neutral, although several theoretical arguments (Banal-Estañol and Ottaviani, 2006; Neuhoff and Vries, 2004) as well as real-world observations suggest that decision-makers in the energy sector are usually risk-averse or at least behave accordingly (Meunier, 2013). This seems to be the case not only for economic but also for political decision-makers (Finon et al., 2008; Neuhoff et al., 2016). However, several studies explicitly consider risk-aversion and their findings are described in the following.

As the electricity market reacts very sensitively to the level of risk aversion of the investors (e.g., Petitet et al., 2017), risk aversion causes the market to deviate from the installed capacity in the welfare optimal case (Winzer, 2013). Given the high social costs of capacity shortages and the uncertainty associated with the development of the electricity market, Vries and Heijnen (2008) point out that the socially optimal level of generation capacity is higher than the theoretical optimum under perfect foresight. Moreover, Ehrenmann and Smeers (2011) find that in an EOM with a low price cap as well as in a CRM, uncertainty and risk aversion aggravates the generation adequacy problem, which in turn can dramatically increase the costs for end consumers. This is caused by delaying investments and shifting from high- to less-capital intensive investments. Similar findings are made by Vries and Heijnen (2008) who state that CRMs can contribute to a more balanced generation portfolio by reducing the investment risk and, thus, counteracting the tendency of risk-averse investors towards low-capital technologies with short lead times. Fan et al. (2012) conclude that a CRM could prove to be beneficial as their findings indicate that risk aversion tempts investors to adopt the decisions that would have been taken if the worst-case scenario had materialized thereby avoiding investments in new uncertain technologies, e.g., concentrating solar power.

As part of an analytical analysis, Neuhoff and Vries (2004) investigate the influence of weather- and demand-related uncertainty and risk aversion on the investment decisions of electricity generators having a unique technology at their disposal. Their results indicate that an EOM will provide insufficient investment incentives to ensure generation adequacy if investors or final consumers are risk-averse and unable to hedge their portfolio adequately via long-term contracts. Maere d'Aertrycke et al. (2017) analyze the effect of two reference long-term contracts as well as the impact of a long-term forward capacity market and find that even though long-term contracts and a highly calibrated forward capacity market are able to improve welfare substantially, they also entail severe drawbacks. In all cases, traded volumes need to be far higher than in current energy markets as illiquidity can severely impair the effectiveness of these instruments and increase the risk premiums demanded by investors by about 10 %. Besides, Willems and Morbee (2010) find that the liquid trade of derivatives provides sufficient incentives for a risk-averse producer to invest. Here, forward contracts mainly lead to an increase of investments in base load capacity, and if also options are offered in the market, the investments in peak-load plants will increase as well. In some cases, if no suitable financial substitutes are traded for an investment option, however, overinvestment can occur.

Furthermore, Abani et al. (2016) state that considering the risk aversion of the decision makers involved is crucial when comparing different market designs. Their results demonstrate that when comparing the implementation of a central buyer mechanism and an EOM, the difference in shortage situations increases if investors are regarded as risk-averse instead of risk-neutral. In a more recent study, Abani et al. (2018) investigate an EOM and two CRMs (central buyer, strategic reserve) and find that in case of risk aversion, investors tend to extend the lifetime of existing generation capacity instead of building new, which in turn leads to higher total generation costs. Similarly, Petitet et al. (2017) show that in an EOM the amount of economically motivated decommissions of thermal plants or the level of scarcity prices is dependent on the risk aversion of the investors. However, CRMs are comparatively insensitive to the risk aversion of the market participants due to the fact that the required quantity is directly specified by the regulator and the risk aversion of the market participants is reflected in their bids affecting the total costs. This proves to be a substantial benefit for policy makers as market developments are more predictable.

5.3.4 Effects of investment cycles

Although fixed or variable capacity payments are unable to abolish investment cycles, they reduce the cycles' amplitude resulting in a high level of market price stability and a reasonable reserve margin (Assili et al., 2008; Ford, 1999). Moreover, Cepeda and Finon (2011) demonstrate that investment cycles can effectively be dampened by capacity obligations, in turn leading to smoother annual average electricity prices and higher reliability.

In case of a strategic reserve, Bhagwat et al. (2016a) and Sisternes and Parsons (2016) find that investment cycles, e.g., caused by uncertainty about the future electricity demand, may still occur. Similarly, Hary et al. (2016) show that although underinvestment is avoided, overinvestment is not prevented by a strategic reserve as the regulator cannot influence the perceived value of additional generation capacity or enforce investors to postpone their decisions. However, a central buyer mechanism is able to positively influence investor behavior and, therefore, reduce the occurrences of under- and overinvestment. Moreover, Bhagwat et al. (2017a) find that in case of a forward capacity market boom and bust cycles may still occur if the electricity demand drops sharply, consequently leading to the decline of capacity prices and multiple decommissions of existing capacity so that only a high reserve margin initially set by the regulator prevents loss of load situations. In reaction to the resulting shortage, capacity prices spike again, and investments are made. Similarly, Bhagwat et al. (2017b) state that in a forward capacity market investment cycles still exist, but in comparison with an EOM, they extend over longer periods and feature smaller amplitudes. Also, by decreasing the investor risk and reliability risk for consumers, forward reliability markets can prevent boom-bust cycles (Cramton and Stoft, 2008).

Beyond, Franco et al. (2015) claim that the implementation of a CRM together with long-term contracts for low-carbon generators prevent any fluctuations in the price and reserve margin in the British electricity market. However, sudden shocks seem not to be taken into account in the analysis. Also, Hasani and Hosseini (2011) state that a hybrid CRM (periodically using capacity payments and a forward capacity market) is able to prevent over- and underinvestment efficiently.

In summary, the presented results support the assertion that investment cycles, which are caused by uncertainties, e.g., regarding the demand growth, can be damped by CRMs (Vries and Heijnen, 2008). However, most often they cannot be completely prevented and a sufficient reserve margin mainly depending on market uncertainties needs to be determined by the regulator.

5.3.5 Efficiency and market welfare of capacity remuneration mechanisms

As a strategic reserve allows the use of all contracted capacities only for a single purpose, inevitably inefficiencies occur, and additional investments are needed to replace the lost flexibility (Höschle et al., 2017). Further, the dispatch of the strategic reserve at any other value than the VoLL can reduce the market welfare analogous to the price caps in the EOM (Finon et al., 2008). Besides, a strategic reserve does not appear to improve the market stability or increase the expected economic surplus in the long term (Lara-Arango et al., 2017a). Therefore, it seems advisable to use a strategic reserve as a short-term solution and replace it by other mechanisms in the long term. However, the distributional effects of a strategic reserve seem to be relatively small (Neuhoff et al., 2016).

Creti and Fabra (2007) state that in order for a CRM to maximize social welfare, gains from reducing load loss situations must exceed the additional capacity costs and the secured capacity procured should be equal to the peak demand. Furthermore, they argue that the price limit should be defined as the opportunity costs of providing full capacity commitment as different parameterizations would lead to a reduction in welfare through either overcapacities or scarcity prices. In a case study for Great Britain, Hach et al. (2016) find that through deliberate overcapacity and, thereby, avoiding extreme prices and lost load occasions, a central buyer mechanism can effectively lower the total bill of generation. Similar results are obtained by Bhagwat et al. (2017b), Höschle et al. (2017), and Keles et al. (2016a) in case studies of the electricity market in Great Britain, Belgium, and Germany respectively. However, Schwenen (2014) argues that in a framework with two firms, in equilibrium capacity prices are non-competitive due to capacity constraints and signals for the entry of new firms are likely being distorted by the regulator.

By employing an analytical model, Briggs and Kleit (2013) find that capacity payments for base load power plants are never optimal. In the short term, capacity payments will cause prices to fall and competitive base load power plants to be suppressed, and in the long term incentives to invest in peak load power plants and generation adequacy will decline. Also, the positive short-term price effect might be lower than theoretically expected (Genoese et al., 2012), and the payments might even fail to ensure an adequate reserve margin (Kim and Kim, 2012; Park et al., 2007). Likewise, Milstein and Tishler (2012) find that targeted capacity payments for the peaking technology, which account for 25 % of the associated capacity costs, only increase the social welfare by 0.02 %. Furthermore, Bajo-Buenestado (2017) show that the benefit of capacity payments depends on the intensity of competition and is less if the market is controlled by dominant companies as in many real-world markets. Joskow and Tirole (2007) state that if market power is present in a market with more than two states of nature, i.e., peak and off-peak, capacity payments are an insufficient instrument.

As results from the literature are not always coherent and often only applicable for specific cases, the question of which CRM is most efficient remains open. For example, often a central buyer mechanism seems to yield significantly better results than a strategic reserve (Hary et al., 2016; Höschle et al., 2017; Keles et al., 2016a), but sometimes the results are ambiguous (Traber, 2017). Most likely, this can be attributed to the fact that the results depend among other things on the existing generation structure and their development in time (Batlle and Rodilla, 2010; Traber, 2017) as well as the taken assumptions, e.g., the consideration of uncertainty (Lara-Arango et al., 2017b) or the risk aversion of investors (Petitet et al., 2017). Nevertheless, there seems to be a consensus in the literature that market-based mechanisms are usually advantageous compared to interventionist mechanisms, e.g., capacity payments (Batlle and Rodilla, 2010; Lara-Arango et al., 2017a; Mohamed Haikel, 2011).

5.3.6 Influence on neighboring markets through cross-border effects

One of the difficulties encountered in the study of cross-border effects is the large number of influence factors such as the regarded markets, generation technologies, different interconnector capacities or asymmetric market sizes. Furthermore, cross-border effects are strongly influenced by competition between market participants and the possibility of exerting market power (Meyer and Gore, 2015). Thus, deriving common conclusions is extremely challenging.

One major short-term cross-border effect is the occurrence of market distortions if a CRM does not adequately consider generation capacities abroad. In this case, through additional capacity payments, domestic producers gain a competitive edge over foreign producers (Hawker et al., 2017). However, the primary focus of the scientific research is on long-term effects, i.e., the development of generation adequacy, distributive effects, and price effects, as CRMs will mainly drive investment decisions (e.g., Ozdemir et al., 2013). For example, with the help of an agent-based electricity market model Bhagwat et al. (2014, 2017c) find that in case of a forward capacity market and strategic reserve in two neighboring markets, the forward capacity market appears to have a negative spillover effect on the strategic reserve. However, a neighboring EOM does not limit the ability of a national forward capacity market or strategic reserve to achieve its objectives. Indeed, vice versa, two effects can be observed. On the one hand, the neighboring EOM operates as a free-rider and benefits from the additional foreign generation capacities. On the other hand, the dependence of the EOM on imports increases, which can be particularly disadvantageous in critical situations. Similar results are obtained by Ochoa and Gore (2015), who show in a case study for the Finnish and Russian electricity market, that if Russian imports were reliably available, abolishing Finland's strategic reserve could lead to lower costs for Finnish consumers. However, as this is not the case, the advantages of maintaining a strategic reserve outweigh the disadvantages, and the interconnection expansion should be avoided—instead, the development of local capacities should be given preference. Furthermore, Cepeda and Finon (2011) find that in the long term an EOM will only marginally benefit from a CRM in an adjacent market. Also, for the EOM, the unilateral introduction of a price cap leads to a reduced level of security of supply as suppliers prefer to offer their generation capacity in neighboring markets. Moreover, by using a simulation model to investigate the unilateral introduction of a strategic reserve and reliability options in a two-country case, Meyer and Gore (2015) show that the overall cross-border welfare effect is most likely negative.

In addition, it can be concluded that the introduction of a CRM in a neighboring country creates considerable pressure on the national regulator to introduce a dedicated CRM as a safeguard against possibly harmful consequences (Bhagwat et al., 2017c; Gore et al., 2016). Therefore, Hawker et al. (2017) are advocating the cross-border coordination of CRMs to provide sufficient new investment in generation and transmission capacities and Neuhoff et al. (2016) claim that a coordinated strategic reserve in Europe should be feasible and, among other things, would have the following advantages: On the one hand, capacities from abroad could be used at times of maximum stress and, on the other hand, the joint calculation of the reserve volume would reduce the required quantity as individual demand peaks usually occur at different times. Furthermore, with the possible expansion of cross-border capacity and the associated strong influence on prices (Osorio and van Ackere, 2016), a coordinated approach seems to be increasingly advantageous. However, solving the dilemma of choosing between a coordinated or national approach is complex. Especially when time is a critical factor, a co-ordinated solution might not be implemented early enough due to the increased need for coordination (Vries, 2007).

5.3.7 Impact of a high share of intermittent renewables

One of the central questions associated with the rapid expansion of RES is whether they exacerbate the adequacy problem. First of all, Cramton et al. (2013) point out that price caps present in most EOMs are unaffected as the level is neither lowered nor increased by RES. Nonetheless, increasing low price caps might become more relevant as large investments in peak-load generation capacity are likely to be required as a backup for intermittent RES. However, this could be prevented by a price cap set too low (Cepeda and Finon, 2013; Jaehnert and Doorman, 2014). As RES, due to their marginal costs close to zero, can be regarded as a price-inelastic demand—with the exception of situations where the prices are negative—Cramton et al. (2013) argue that RES increase the volatility of and the uncertainty about the demand and market prices and, thereby, exacerbate the adequacy problem. Similarly, Newbery (2017) claims that a high share of intermittent RES, on the one hand, and the uncertainty about the development of the carbon allowances price, on the other hand, likely require long-term capacity contracts—beyond a horizon of three to four years—for ensuring reliability efficiently.

Jaehnert and Doorman (2014) investigate the development of system adequacy and find that the capacity reserve margins decrease with an increasing share of RES leading to several occurrences of load curtailment. Also, the merit-order effect caused by large-scale employment of wind energy is more relevant in an EOM than in a market with a CRM, where thermal generation capacities are better able to recover the fixed costs of their investment (Cepeda and Finon, 2013). However, in reverse, a CRM that only takes into account the secured available capacity can have a negative impact on the market-driven development of wind power. Still, in a world with 100 % renewable energy, Weiss et al. (2017) argue that an EOM can adequately function if market prices take into account the opportunity costs of flexible resources. However, in such a scenario, RES probably still require a dedicated funding mechanism. Besides, a CRM might be necessary to minimize the associated risk of underinvestment in flexible capacities.

5.3.8 Incentives for flexible resources

As with increasing shares of RES supply fluctuations in the electricity market become more frequent, flexible resources are required (Grave et al., 2012; Nicolosi, 2010), e.g., demand-side management or short-term and long-term storage options that have not yet been sufficiently remunerated in the market design to date (Cepeda and Finon, 2013; Joskow, 2008). An adequate market design needs to pay sufficient attention to flexible resources in order to fully capitalize on their potential (Neuhoff et al., 2016; Weiss et al., 2017). Although flexible resources do not automatically guarantee a reliable level of investment, they ensure reliability under different levels of installed generation capacity and induce an efficient electricity dispatch (Cramton and Stoft, 2005).

Whereas the concept of firm or reliable capacity is already well defined and, moreover, constant, regardless of how the future electricity system develops, the term flexibility is still vague and furthermore has a critical temporal dependency. Sometimes flexibility is required for a few seconds or minutes, but other times for several hours or even days and usually the most suitable options for short-term flexibility are not coherent with those for long-term flexibility (Hogan, 2017). In order to reliably determine the need for and value of flexibility, it is best to compare the value of energy in scarcity with that in abundance situations, which depends on the current state of the electricity system.

In a well-functioning EOM, market participants are exposed to extremely high price signals at times of scarcity or negative prices in times of oversupply, thus, creating incentives for long-term investments in storage technologies as well as incentives for consumers to directly react to price developments (e.g., Hu et al., 2017). For this reason, EOMs can especially benefit from increased flexibility, e.g., through demand response, as the market is then able to react to extreme price peaks and consumers are no longer exposed to the excessive market power of suppliers, thereby reducing the need for regulatory price caps (Schwenen, 2014). Yet, if the market design is severely different, e.g., by a forward capacity market, price spikes will decrease in frequency and amplitude, thus, diminishing the value of flexible resources (Hogan, 2017). Auer and Haas (2016) even argue that the introduction of capacity payments ruins market competition, meaning that flexibility options would not be exploited, thus, leaving their development only in the hands of the regulator. Even though these theoretical findings pose a clear disadvantage for CRMs, practical experiences indicate that decision makers seem to be aware of this issue as, for example in the US, CRMs explicitly include financial support for flexible resources, which in turn lead to a rise of these capacities (Rious et al., 2015).

5.4 Conclusions and policy implications

Electricity markets are in many respects similar to most other markets; however, they require a specific regulatory framework due to a number of peculiarities such as the physical characteristics of the commodity electricity, an inelastic volatile demand and the missing-money problem. In combination with the transformation from a centralized system with primarily fossil-fuel power plants to a decentralized system with a high share of renewable energies and the sharp decline in electricity prices, concerns among policy makers about generation adequacy have grown and led to the implementation of various CRMs. However, the necessity of CRMs remains the subject of ongoing discussion, and it is often argued that an EOM already offers an efficient solution whereas CRMs tend to be inefficient. To better grasp the arguments of both sides, an up-to-date overview of the debate was given. Subsequently, a classification of the different mechanisms was shown, the current status of real-world implementations was presented, and initial experiences were discussed. Whereas only two types of mechanisms (central buyer and de-central obligations) are used in the United States, the situation is much more diverse in Europe due to uncoordinated national approaches.

The findings in the literature reveal that CRMs can improve generation adequacy, but also bring along new challenges. One major advantage of CRMs is that they are able to effectively reduce or even to solve different problems of existing markets. For example, fluctuations caused by investment cycles can be dampened—even though usually not fully abolished—and, thereby, extreme scarcity events can be prevented. Also, the adverse effects of the abuse of market power can be mitigated, and some mechanisms, for example, a forward capacity market, are able to solve the missing money problem. Also, CRMs usually make market developments less dependent on the risk profile of the investors, thereby, making them more predictable and reducing deviations from the long-term optimum that can be caused by risk-averse decision-makers.

Determining the optimal market design, however, remains an ongoing challenge. As the adequate design depends on a variety of factors such as the existing capacity mix and demand characteristics, no general advantageousness of single mechanisms could be determined so far. For example, often a central buyer mechanism seems to yield significantly better results than a strategic reserve, which is inefficient by design as contracted capacities are used for a single purpose only. However, in exceptional cases the results are ambiguous. Nevertheless, it can be concluded that market-based mechanisms, e.g., a forward capacity market, are usually advantageous compared to interventionist mechanisms such as capacity payments.

Furthermore, the implementation of a CRM can lead to market distortions, e.g., through cross-border effects. Even though cross-border impacts are diverse and the results in the literature are sometimes conflicting, there seems to be a consensus that a one-sided implementation of CRMs leads to negative spillover effects on a neighboring market without a CRM. This increases the pressure in the neighboring market either to introduce a domestic mechanism or to pursue a coordinated approach. Compared to an EOM, the value of flexible resources is diminished in the presence of a CRM.

Therefore, their expansion is largely independent of market forces and left in the hands of the regulator.

Even though a large number of studies has already been carried out, the comparability of the results is often limited and, thus, it is difficult to select the best mechanism to implement. It would therefore be helpful if common criteria or specific scenarios are used to evaluate different market designs. Furthermore, especially the efficiency of the mechanism is all too often neglected. Also, the behavior of market participants as learning, risk-averse agents that interact with each other often does not seem to be adequately addressed and rarely verified by studies or experiments. However, as the investors' risk profile can directly influence the results and the relative advantageousness of different CRMs, it would thus be advisable to explicitly consider risk aversion.

5.5 Details on selected real-world implementations of CRMs

In the following, some details on real-world implementations of CRMs additional to the information already presented in Section 5.2.2 is provided. Not all mechanisms active around the world are described, but the focus rather lies on the mechanisms currently active in Europe as well as the different central buyer implementations in the United States, which is the most common type of CRM used in Northern America.

Strategic reserve (Belgium/Sweden)

Both Belgium (since 2014) and Sweden (since 2003) have set up strategic reserves to support demand peaks during the winter season (Elia, 2015; Svenska Kraftnät, 2016). In Belgium, the capacity is procured through a competitive tendering process, in which market participants intending to shut down capacity are obliged to participate (Hancher et al., 2015). Thus far (until October 2017), the reserve has not been activated (Elia, 2017a,b). Contrary, the Swedish reserve has already been used a few times, with yearly costs in 2013 and 2014 amounting to about 14 respectively 13 million Euro. This is significantly lower than the estimated costs of a shortage situation (90 million Euro) (Cejie, 2015).

Central buyer (United Kingdom/US – ISO-NE/US – MISO/US – NYISO/US – PJM)

In order to maintain generation adequacy, in 2014, the United Kingdom introduced central capacity auctions with the first delivery to take place in winter 2018/2019. The capacity payments are determined via descending clock auctions four years (T–4) and one year (T–1) before the respective delivery period. Despite the technology-neutral approach, the incentives for demand response (0.4–2.5 % of the contracted capacity) and new investments (4.2–6.5 %) have been limited in the first three T–4 auctions (Ofgem, 2015, 2016, 2017). However, in the latest T–4 auction (2016), existing and new storage capacities won contracts for the first time, accounting for around 6 % of the contracted capacity (Ofgem, 2017).

ISO New England (ISO-NE) and New York ISO (NYISO) were the first market areas in the United States to use central capacity auctions as early as 1998 and 1999, respectively. A few years later, PJM Interconnection LLC (PJM) (2007) and Midcontinent ISO (MISO) (2009) also introduced such mechanisms in their market areas. All four implementations have in common that capacity is procured in multiple zones in order to account for intra-zonal transmission constraints (Byers et al., 2018). The auction design, however, differs among the mechanisms. While uniform pricing is applied in PJM and NYISO, ISO-NE and MISO use descending clock auctions (Bhagwat et al., 2016b). Moreover, ISO-NE is the only mechanism bundling capacity options with financial call options (similarly to the reliability options model proposed by Vázquez et al., 2002), while NYISO, PJM and MISO conduct forward capacity markets. An overview of the historical capacity prices of the four markets is provided in Byers et al. (2018), although the authors state that clear trends could not be identified due to the limited amount of data points as well as differences and changes in markets rules.

De-central obligation (France)

In 2015, France implemented a de-central obligation with the first delivery to take place in 2017. All load-serving entities are obliged to hold a certain number of certificates reflecting the share of electricity consumption of their consumers during times of peak demand, e.g., when extreme winter conditions occur. Certificates can be obtained by certifying own generation and demand-side capacities, which afterward can be traded in a market or using bilateral arrangements (European Commission, 2016a). Within Europe, the French mechanism is the first to explicitly include and remunerate foreign capacities in neighboring countries, however, limited by the expected capacity of the respective interconnectors at peak times (European Commission, 2016d). In the first three auctions, a total volume of 34 GW has been contracted with all auctions resulting in capacity prices close to 10 000 EUR/MW (EPEX SPOT, 2017d,e,f).

Targeted capacity payments (Spain)

The Spanish mechanism, initially introduced in 1997, was substantially redesigned in 2007 to adapt to the then valid European law (Hancher et al., 2015). The new system was designed to reduce investment risk by offering fixed capacity payments for a period of ten years (investment incentive). Securing generation adequacy in the medium-term (availability service) through contracts of one year or less with peak-load power plants was the other main target. However, to estimate the required generation capacity and long-term capacity payments was made significantly more difficult by unforeseen events like the economic crisis and the resulting low electricity demand, which together led to the reduction of long-term capacity payments for investments in 2012 and ultimately to the abolition of the investment incentive in 2013. Nonetheless, the availability service is still active.

Chapter 6

An agent-based model of the German day-ahead market

Since the deregulation of electricity markets that in Europe started in 1996 based on the Directive 96/92/EC, national markets gradually evolved from integrated monopolies to liberalized markets. Although at that time optimizing models were widespread and used to assess electricity system related questions in monopolies, these models did not account for market aspects, which brought forward the development of agent-based electricity market models, in which players like companies or the government are represented by agents that continuously interact with each other, autonomously pursue their own goals and possess their own set of private information (Tesfatsion, 2002). Thus, results from agent-based are evolved step-by-step and are the outcome of all interactions between the different agents. Initially, agent-based models were limited to rather simplified cases, but with the increasing availability of computational resources, researchers were enabled to develop large-scale models with a high degree of flexibility and the detailed consideration of techno-economic restrictions (Weidlich and Veit, 2008). Agent-based models are able to analyze imperfect markets such as oligopolies that often times occur in electricity markets, e.g., in Germany where currently four companies—Energie Baden-Württemberg AG (EnBW), E.ON SE (E.ON), RWE AG (RWE) and Vattenfall GmbH (Vattenfall)—own more than 80 % of the thermal generation capacities (Bundeskartellamt, 2011). In Germany, the electricity market has undergone major changes due to the phase-out of nuclear energy and the rise of renewable energies, which have been promoted via the Renewable Energy Sources Act (Erneuerbare-Energien-Gesetz) that provides fixed feed-in tariffs based on the renewable technology and guarantees priority feed-in into the grid. Especially the capacities of wind and photovoltaic power plants have experienced a sharp rise which poses a challenge to the generation companies that have to cope with the uncertain feed-in from these sources. With a total installed capacity of 33 GW of photovoltaic and 31 GW of wind power plants in 2012, the highest difference between the official day-ahead forecast on a national level and the real-feed in was 6 GW and 7 GW respectively (EEX, 2018b). In the current market design, these deviations have to be taken care of by the transmission grid operator who first tries to balance the deviations by trading in the intraday market and afterward by requesting balancing energy.

There already exist numerous large-scale electricity market models. One of the first models was already developed in 2001 for the electricity market of Wales and England and already included a forward market as well as balancing mechanism but only a single day was modeled (Bunn and Oliveira, 2001). An application for the U.S. electricity market can be found in Li et al. (2011b). Recent models also contain grid restrictions, e.g., for the German market area (Veit et al., 2009). Whereas in most model uncertainties are not explicitly regarded, in Li and Shi (2012) an agent-based model is presented where generation companies have to cope with the uncertain feed-in from wind power plants in a locational marginal pricing scheme. The generation companies learn from their past experience and try to improve their bidding strategy. Other uncertainties apart from the wind feed-in are not regarded.

A critique often stated in regard to the agent-based modeling approach is that only few guidelines exist to validate agent-based models and therefore models lack proper empirical validation on an aggregate level. Also, not enough information about key parameters is provided so that results are not reproducible (Weidlich and Veit, 2008). Nevertheless, the explanatory power of agent-based models has been proved when validation is performed. Thus, agent-based models are a valuable tool to assess electricity-market related question (Sensfuß et al., 2008).

The structure of this chapter is as follows: In Section 6.1 the model is introduced with its main characteristics. Then, in Section 6.2 an overview of the input data of the model, such as power plants or demand is given. Section 6.3 reports the simulation results and the model validation. Finally, Section 6.4 summarizes the main results and concludes.

6.1 An agent-based model with uncertainty factors

In this model, the German day-ahead electricity market with its relevant players, e.g., traders, generators and market operators, is replicated. Generators and consumer are called by a market operator to submit their bids for the next day. The hourly demand is bidden by the demand trader; whereas the generation companies submit bids for their thermal generating capacities and the expected renewable feed-in is bidden by the grid operator. After all agents have submitted their bids, the market is cleared, and each agent receives its accepted bids as well as the hourly market price. In the following, the different parts of the model are described in detail.

6.1.1 Demand

Although the short-term electricity demand can be regarded as rather inelastic, in this model, a limited elasticity of the demand has been used. This is due to the fact that the model is restricted to the German market area. The supply or demand of neighboring countries is included as a static hourly value whereas in reality the exchange is influenced by the market price, e.g., if the demand in Germany is relatively low, additional generation capacities may be available which run at lower costs than power plants a neighbor country and therefore additional electricity is exported. Hence, the demand is also influenced by the market price. In the model, the elastic demand is defined as:

$$D_t\left(P_t\right) = D_t^* \cdot \left(\frac{P_t^*}{P_t}\right)^{\epsilon} \tag{6.1}$$

with D_t^*, P_t^* and ϵ denoting the historical demand, the historical price, and the price elasticity. Similar to Traber and Kemfert (2011), an elasticity parameter of $\epsilon = 0.9$ has been used for the simulation in Section 6.3.

6.1.2 Supply

In order to account for start-up costs, generation companies have to forecast how long their power plants will be in the market. The bidding algorithm can be divided into several steps (see Figure 6.1), where each main step is described in the following paragraphs.

Price forecast

Three factors mainly influence the uncertainty in the day-ahead market: First, the exact demand of the next day, second, the renewable feed-in and third, unexpected outages of power plants. In the model, each uncertainty factor is represented by different scenarios. For the demand and the renewable feed-in, three scenarios for the next day are created: high, medium and low. For the unexpected outages, two scenarios are created. In one scenario, all power plants are available, and in the other scenario, different randomly selected power plants are unavailable. Each combination of scenarios is then used as a scenario for which a price forecast is performed.

Hourly bids

Based on the different price forecasts and the variable costs of a power plant for each hour it is assumed that the power plant is in the market if the power plant's variable costs are below the price forecast and otherwise out of the market. The variable costs are defined as:

$$c_{d,i}^{\text{var}} = \frac{p_{d,i}^{\text{fuel}}}{\eta_i} + \frac{EF_i}{\eta_i} \cdot p_{d,i}^{\text{cer}} + c_{d,i}^{\text{other}} \tag{6.2}$$

where $p_{d,i}^{\text{fuel}}$, $p_{d,i}^{\text{cer}}$, EF_i, η_i, and $c_{d,i}^{\text{other}}$ denote the fuel price, the carbon price, the fuel emission factor, the efficiency and the variable operation and maintenance costs.

The start-up costs consist of two parts. One part is related to the fuel and carbon certificates needed for the ramping process, and the other part is related to the deprecation caused by the ramping process. Hence, the start-up costs can be expressed as:

$$c_{d,i}^{\text{start}} = r_i \left(p_{d,i}^{\text{fuel}} + EF_i \cdot p_{d,i}^{\text{cer}} \right) + d_i \tag{6.3}$$

with r_i and d_i denoting the ramping parameter and the deprecation parameter. The start-up costs also depend on the hour of the start-up and the last running hour. In the model three different start-up costs—hot, warm, and cold—are distinguished:

$$c_{d,h,i}^{\text{start}} = \begin{array}{ll} 0.3 \cdot c_{d,i}^{\text{start}} & h \leq 8 \\ 0.5 \cdot c_{d,i}^{\text{start}} & 8 < h \leq 48 \\ 1.0 \cdot c_{d,i}^{\text{start}} & \text{h} > 48 \end{array} \tag{6.4}$$

where for the warm and hot start-up costs a fraction of the cold start-up costs were chosen similar to Grimm (2007). Whereas the variable costs are the same in all scenarios, the start-up costs can differ for each scenario. In order to determine how the start-up costs are included in the bids, first, for each scenario the start-up costs are evenly distributed over the period where the power plant is expected to be in

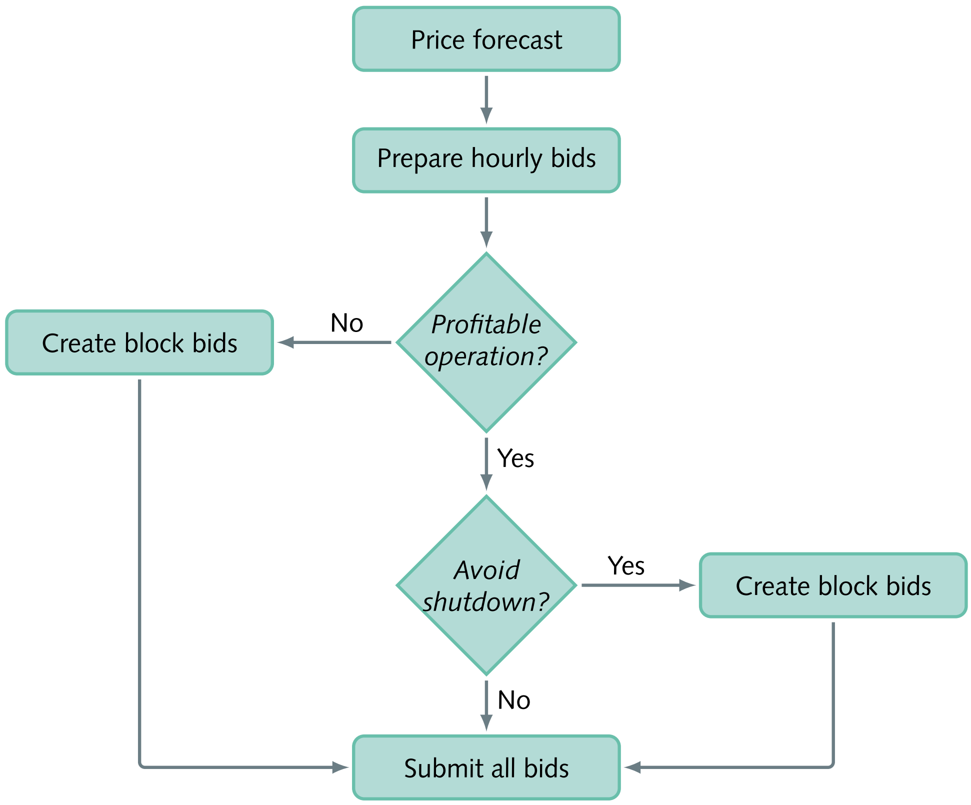

Figure 6.1 | Sequential diagram of the bidding process. After the electricity price scenarios are forecasted, first hourly bids based on the variable costs of each plant are prepared. If a power plant is not expected to be on the market at all, block bids are made to ensure that the start-up costs are earned in the event of unexpected short-term operation. For an expected operation with shorter interruptions, block bids can be created, which allow a continuous operation and avoid start-up costs.

the market based on the variable costs, e.g., if a power plant is supposed to be in the market for three hours in one scenario, each hour contains one third of the total start-up costs. Second, the expected distributed start-up costs are calculated as the average value over all scenarios. Then, for each hour where the power plant is expected to be in the market at least once, an hourly bid is submitted:

$$bid(h, p, v) \tag{6.5}$$

where h denotes the hour, p price and v the volume of the bid. The price of the bid is equal to the variable costs and the expected distributed start-up costs.

Avoided turn-off bids

If a power plant is expected to be out of the market for a short period of time, in order to avoid a shutdown a market price below its variable costs might be accepted. This is even more relevant when a power plant due to technical constraints is not flexible enough to ramp down and up in the out-of-market period. In the model, each power plant i has a minimum downtime. For the electricity generator, it is important that an attempt to avoid a shutdown is either entirely successful or completely unsuccessful. A partial success would result in shutting down the power plant as well as producing below variable costs. Therefore, a block bid is submitted by the generation company which only can be fully accepted in each hour or not at all:

$$bid(h_s, h_e, p, v) \tag{6.6}$$

where h_s, h_e, p, and v denotes the first hour, last hour, hourly price and volume of the bid. The hourly price p of the block bid equals the variable costs $c_{d,i}^{\text{var}}$ minus the avoided start-up costs:

$$c_i^{\text{avoid}}(h) = \begin{cases} c_{d,h,i}^{\text{start}} \cdot \frac{1}{h} & \text{if } h > h_i^{\min} \\ c_{d,h,i}^{\text{start}} \cdot \frac{1}{h} \cdot \frac{h_i^{\min} \cdot c}{h} & \text{else} \end{cases} \tag{6.7}$$

with h, $h_i^{\min}$, c denoting the number of hours the unit is out of the market, the minimum downtime and a cost parameter. Although the minimal out-of-market time does not represent a hard technical limit, it can be seen as an economic limit, as the generating company wants to avoid excessive thermal stress that would significantly

Table 6.1 | Mark-up actions and scarcity states. To ensure effective learning, the action and state space must be restricted. In this case, five actions and states are permitted. For each state, agents can choose between no markup at all up to the maximum value of 15 EUR/MWh.

Actions [EUR/MWh]	0	3	6	9	15
Scarcity states [-]	(0.5,0.6]	(0.6,0.7]	(0.7,0.8]	(0.8,0.9]	(0.9,1.0]

lower the unit's lifetime. In case the out-of-market period is shorter than the minimal out-of-market time, the generation company is willing to lower its bid price by an amount greater than the start-up costs. This amount is related to the ratio of minimal and expected out-of-market time as well as the cost parameter c. For the simulation in Section 6.3, the parameter c takes a value of two, with which historical results could be reproduced adequately.

Learning and Mark-up

The generation companies can increase their bids by a markup. The markup is chosen from a list of discrete values and depends on the hourly scarcity of the market. The scarcity is expressed as the ratio of demand to capacity for which five different states are distinguished. In all states all actions can be chosen; only if the scarcity ratio is less than 0.5 no markup is applied. The different actions and states can be found in Table 6.1. The actions are then determined via a reinforcement learning algorithm based on Nicolaisen et al. (2001).

6.1.3 Market clearing

In a first step, all bids—hourly bids and block bids—are aggregated into linearly interpolated supply and demand functions, where the volume and price of each bid is taken into account. Block bids that either have to be accepted or rejected in each hour are split into hourly bids that can be accepted or rejected independently from each other. The preliminary market price then results from the intersection of the supply

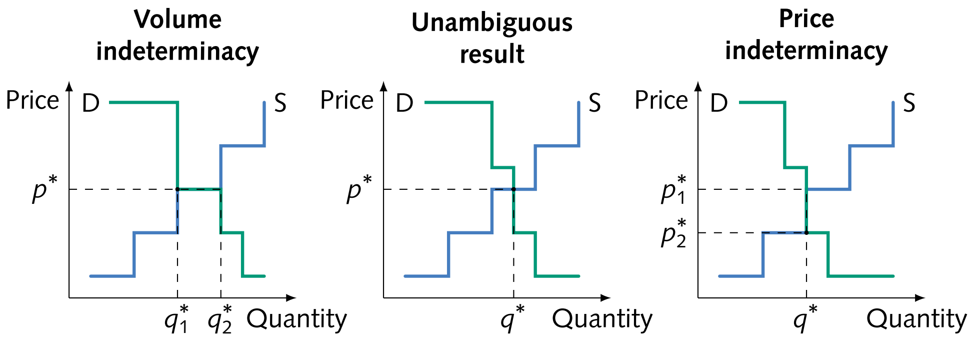

Figure 6.2 | Market clearing. Three different situations can be distinguished: *volume indeterminacy*, *unambiguous result* and *price indeterminacy*. In the case of volume indeterminacy, the set of possible volumes is limited to the interval $[q_1^*, q_2^*]$; in the case of price uncertainty, the interval $[p_1^*, p_2^*]$ can be specified. In these situations, the model proceeds as follows: In the first case, the traded volume is maximized, whereas in the second case, the center of the price interval is selected. *Source:* EPEX SPOT (2011a).

and demand function. As a second step, the profit for each block bid is calculated based on the preliminary market prices. The block bid that shows the highest loss is rejected. In case two block bids share the same loss, only the block bid with the lower volume is excluded. Afterward, the preliminary market prices are recalculated as described in the first step and another block bid is excluded. This procedure is repeated until all block bids are profitable. If the intersection of the supply and demand function is not a single point but an interval, the market outcome is indeterminate, and specific rules need to be defined. For the model, rules of the market clearing mechanism at the EEX were adopted (see Figure 6.2).

6.2 Required data

Due to the fact that reliable input data are central to obtain reliable results, all data has been carefully selected. In the following paragraphs, the different data sources are described in detail.

For Germany, the Federal Network Agency provides a list of all power plants of a capacity larger than 10 MW. This list contains useful specifications such as the net capacity and owner of each power plant, but not all parameters relevant for the applied model, e.g., the efficiency are included. Therefore, the missing parameters need to be researched. In particular, for newer power plants plenty of information is publicly accessible, but in case some parameters were not retrievable, an estimation based on the technology and initial date of operation was performed similar to Genoese (2010).

According to the European Network of Transmission System Operators (ENTSO-E), the yearly consumption in Germany in 2011 amounted to 544.2 TWh (ENTSO-E, 2018b). Consumption values are available on a monthly level only, but for the model hourly values are required. Hourly load values are available which, however, are not as precise as the monthly consumption values. Therefore, the hourly load values were taken and scaled so that they represent the total yearly consumption.

In 2011, Germany exported more electricity than it imported with a resulting net exchange of 6.2 TWh (ENTSO-E, 2018b). This equals 1.1 % of the national consumption. As the model's spatial resolution is restricted to Germany, the exchange with neighboring countries has to be given exogenously. The hourly exchange values were taken from electricity transparency platform of the ENTSO-E and correspond to the cross-border physicals flows (ENTSO-E, 2018b). The cross-border commercial schedules would have been an even better choice to represent the exchange the generation companies expect when bidding in the day-ahead market, but those values were not available consistently for the year 2011.

In this model, daily prices for emission allowances, hard coal, natural gas and oil are integrated. Natural gas, hard coal, and allowances prices are taken from the EEX. The

Table 6.2 | Start-up costs. The start-up costs vary considerably from technology to technology in terms of both the deprecation and fuel factor. Of these factors, the fuel factor is decisive one, which means that the technologies with the lowest value, i.e., Gas GT/IC and Oil IC, usually exhibit the lowest start-up costs. *Source:* Traber and Kemfert (2011).

	Deprecation [EUR/MW]	Fuel Factor [MWh/MW]
Coal New	5.0	6.2
Coal Old	1.5	6.2
Gas CC	10.0	3.5
Gas GT	10.0	1.1
Gas ST	10.0	4.0
Gas IC	10.0	1.0
Lignite New	3.0	6.2
Lignite Old	1.0	6.2
Nuclear	1.7	16.7
Oil GT	5.0	1.1
Oil ST	5.0	4.0
Oil IC	5.0	1.0

daily oil price is provided by the European Central Bank. Whereas for the allowances and natural gas daily spot prices are available at the EEX, this is not the case for hard coal, which is only traded via futures as coal cannot be delivered fast enough in larger quantities. Thus, the daily coal price is approximated via the coal future for the next month whose trading date is closest to the simulated day.

The parameters for the start-up costs in Equation (6.3) are not publicly available on the plant level and, hence, have to be estimated. Here, the values from Table 6.2 are used, which are based on Traber and Kemfert (2011).

The expected and actual generation of wind and photovoltaic power plants is taken from EEX (2018b). The feed-in of other renewable technologies, though not publicly available, is based on selected profiles whereas the total yearly production equals the

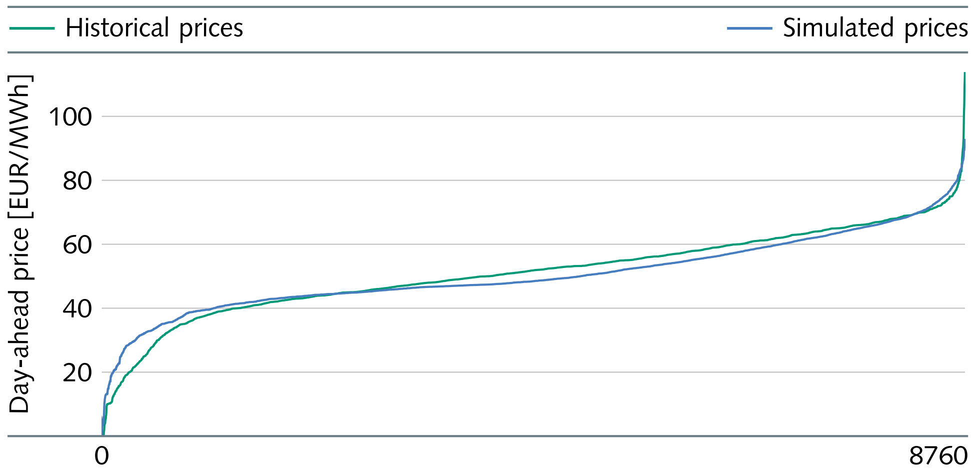

Figure 6.3 | Annual price curve. The sorted simulated and historical price curves show high similarity. Deviations are mainly noticeable in the range below 40 EUR/MWh when only base-load power are running and, in the model, prices decrease comparatively late. *Sources:* EPEX SPOT (2018b).

values from BMWi (2018c).

6.3 Simulation and validation of the results

The proposed computational model described in Section 6.1 enables to thoroughly analyze the German electricity market. In the following, a simulation for each hour of the year 2011 is discussed, and an empirical validation of the results is performed at an aggregate level. As valid input data are crucial to achieve reliable model results, data were carefully selected as described in the previous section. However, some data, e.g., the outages of power plants, is not publicly available at the plant level. Thus, deviations between input data and historical data can negatively impact the quality of the results. Figure 6.3 gives an overview of the sorted historical and simulated hourly prices showing that the proposed model is well capable of reproducing historical prices. In Figure 6.4 the simulated and historical hourly prices of the first fourteen

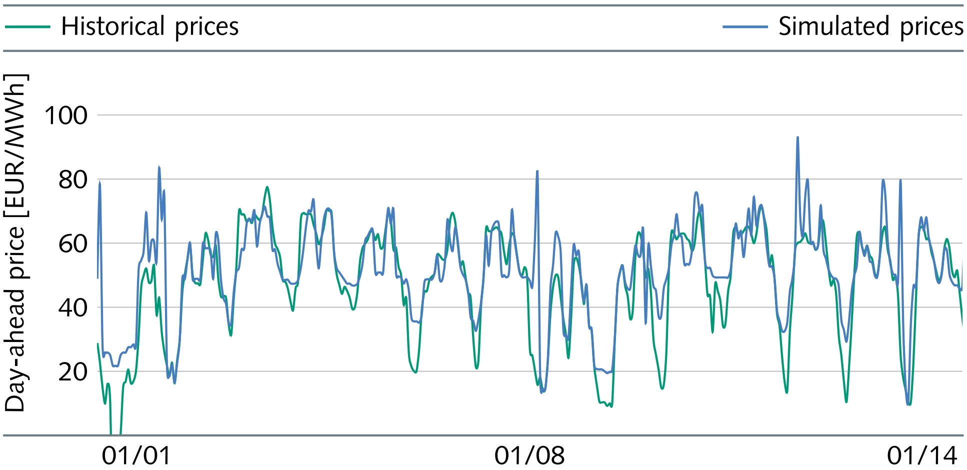

Figure 6.4 | Chronological price development. The simulated and historical prices for the first fourteen days of January in 2011 show a similar daily pattern. Whereas the upper price peaks are usually reached or even exceeded, not all negative price peaks are matched in the simulation. *Sources:* EPEX SPOT (2018b).

days of the year 2011 are depicted, which exhibit a similar structure. To further validate the model, different statistical figures are calculated which can be found in Table 6.3.

The mean in the model of 50.56 EUR/MWh is slightly lower than the historical mean of 51.12 EUR/MWh, but their difference is comparatively small. Also, the standard deviation in the model is slightly slower than the historical standard deviation. This is related to the number of prices below 30 EUR/MWh, which is less than in historical prices. Low prices are influenced by must-run power plants that for example provide heat supply and therefore cannot be shut down. This is currently not accounted for in the model. Furthermore, the assumption that there exists potential to increase the export into foreign market areas may not hold to be true at all times. This potential can increase the load in low load situations and, hence, as well increase market prices.

The historical and simulated minimum prices differ by 26.95 EUR/MWh. Given that the fourth lowest historical price equals −10.1 EUR/MWh, the minimal simulated price of −9.86 EUR/MWh seems to be reasonably close. The same is the case for the maximum prices, where the difference between historical and simulated values equals

Table 6.3 | Statistical figures. For the year 2011, the simulated and historical figures closely resemble each other. However, as it is often the case, the fundamental model can well represent typical situations, but cannot explain the most extreme values, some of which might be caused by non-fundamental factors such as human behavior.

Figures	Unit	Historical	Simulated
Mean	EUR/MWh	51.12	50.56
Standard deviation	EUR/MWh	13.60	11.86
Minimum	EUR/MWh	–36.82	–9.86
Maximum	EUR/MWh	117.49	98.84
Correlation	–		0.77
MAE[a]	EUR/MWh		2.25
RMSE[a]	EUR/MWh		2.93

[a] These figures are calculated based on the sorted historical and simulated prices.

18.65 EUR/MWh, but only thirteen historical prices exceed the maximum simulation price.

The Pearson correlation coefficient of the unsorted hourly prices equals 0.77. This value indicates a high dependence of the price paths as it can also be seen in Figure 6.4, where the correlation equals 0.79. The MAE of 2.25 EUR/MWh and the root-mean-square error (RMSE) of 2.93 EUR/MWh can be considered as very low. In comparison, a MAE of 4.26 EUR/MWh and a RMSE of 8.91 EUR/MWh are considered to be excellent for a bottom-up electricity market model (Barth et al., 2004). Likewise, for a German electricity-market model, a MAE of 7.00 EUR/MWh and a RMSE of 8.83 EUR/MWh is reached for the year 2010 (Genoese, 2013).

6.4 Conclusions and implications

In this chapter, an agent-based model for the German electricity market has been introduced that accounts for short-time uncertainty factors such as power plant outages and fluctuating renewable sources. The model is based on detailed input data such as daily prices for carbon, hard coal, natural gas, and oil as well as hourly values for the national demand and the renewable feed-in. The model's database also contains each power plant with a capacity of more than 10 MW. A simulation for each hour of the year 2011 was performed. The validation shows that the model is able to adequately simulate historical peak and off-peak market prices. Although the range of simulated prices is a slightly smaller than the historical price range, negative prices do occur due to start-up costs and technical restrictions of power plants, e.g., start-up times or minimal out-of-market times. In order to account for start-up costs, generation companies need to forecast when their power plants will be in the market. Here, the integration of uncertainty via different residual load scenarios enables the generation companies to better cope with deviations from their expectations. Due to the increasing share of fluctuating renewable energies in Germany, short-term uncertainties are having a growing impact on the day-ahead market, and the importance of explicit consideration in fundamental models is further increasing.

Compared to the historical values, the number of hours in which base-load power plants determine the market price is significantly lower within the performed simulation. As base-load power plants determine the market price in low demand situations, these cases must be analyzed in greater depth. In this context, it is critical to account for must-run capacities that for example supply heat to the local industry or housings and therefore cannot be shut down. Another important area for future research is the interdependence of day-ahead markets and other markets, such as reserve markets and intraday markets.

Chapter 7

Analysis of design options for the electricity market: The German case

After intensive discussions in the past years, some European countries, e.g., Belgium, France, and the UK have implemented capacity mechanisms. Germany decided to adjust the design of its electricity market (EOM) by introducing a capacity reserve, which is similar to the strategic reserve mechanisms found in some other European countries (e.g., Belgium, Sweden). Major changes such as the implementation of a capacity market are rejected under the current proposal of the electricity market act (in German: "Strommarktgesetz," see BMWi, 2018c). However, the appropriate market design remains a controversial issue.

The reason for that are ambiguities regarding whether the current EOM can provide sufficient incentives for investments in flexible generation technologies to ensure the long-term security of supply. The wholesale electricity prices have been comparatively low, which can be explained by different factors. Firstly, there are surplus capacities originating from times before the liberalization of the energy market. The surplus increased due to the large-scale introduction of renewable energies in addition to the coupling of European market areas. And secondly, the currently low price for carbon emission certificates and natural coal lead to low electricity prices, thereby favoring coal-fired power plants and causing gas-fired power plants to be less competitive.

As the electricity feed-in from intermittent renewable energy sources rises (e.g., Ederer, 2015), the operating hours of conventional power plants subsides. Their revenue situation worsens considerably. However, flexible conventional backup capacities might still be necessary, especially when peak load times overlap low feed-in from PV and wind power. This raises the question whether the marginal cost based EOM provides enough incentives for investments in new power plant capacity or whether a capacity market should be introduced as a new market segment for the product secured capacity.

Besides providing sufficient capacity in peak load times, the new market design also aims for other objectives. This includes both the elimination of local supply (grid) bottlenecks within Germany and the conversion of the electricity system towards a more flexible one with sufficient power generation and storage capacity. The latter is especially important concerning the objective of the federal government to generate 80 % of electricity from RES by 2050. Predominantly, flexible capacity such as gas turbines and energy storages, or demand-side management (DSM) measures will be required in the future, in addition to the volatile generation of renewable energies. These different objectives also influence the configuration of the future market design and the parameterization of a capacity mechanism (Mastropietro et al., 2016).

The need for more significant changes to the EOM design and the introduction of a capacity market are still not sufficiently analyzed, especially based on simulative approaches. Existing studies are based on optimization or Cournot equilibrium models (Léautier, 2016; R2B, 2014), focusing on a system analysis from a central planner perspective. However, the electricity system changes to a more decentralized one with different market players that follow their own targets. This can differ from the objectives of a central planner or the regulator. Besides, market players have to make decisions with limited foresight of future developments. This study, therefore, focuses on individual decisions and investment behavior of market players. The agent-based analysis of the effectiveness and cost efficiency of different market design options is done by paying attention to the specific decisions of stakeholders and their limited foresight (especially of the major power plant operators and the regulator). Another advantage of agent-based simulation is that it allows the determination of market failures, especially possible capacity gaps (e.g., the power plant operators do not realize sufficient investments to cover peak demand). In contrast to optimizing energy or electricity system models, there is no restriction in the agent-based approach that the demand has to be met in each time step (energy balance constraint). Therefore, in this approach, the total capacity derived from the single investment decisions can be lower than the required capacity to meet the peak demand consistently. This characteristic of the agent-based simulation approach allows for the analysis of generation adequacy, as a possible lack of generation capacities due to less investment activity of market agents can be directly determined from the output of the model.

This chapter introduces a powerful method to analyze the effectiveness and cost efficiency of market design regulations that are intensively discussed not only in Germany but also in other European countries like France, Belgium, and the UK. The effectiveness of a market design is defined by its ability to trigger investments in power plants or other flexible capacity and to serve the demand for electricity through generation capacity in every point of time. Besides, the effectiveness and cost efficiency (the overall system costs of electricity supply) in each market design are also analyzed in this chapter.

The analysis of various market design options can support policy makers in their decisions on new regulations for the electricity market. It primarily provides insights about circumstances under which an EOM still can guarantee the security of supply, especially generation adequacy, and at which time the introduction of a capacity market could be more advantageous. This study may also help energy supply companies to recognize the impact of different market regulations on their investments and to understand at which point of time new investments could become economically feasible.

To achieve these goals, the chapter is structured as follows: Section 7.1 gives an overview of the most recent literature on the security of supply, in particular regarding the required power plant capacity to meet the demand. The focus here is also on market designs that are favored to guarantee generation adequacy. This is followed by a detailed overview of the proposed market design options for the German electricity market (Section 7.2).

Section 7.4 describes the applied agent-based modeling approach for the German electricity market. In the case of an EOM market design, it focuses on investment agents, who make their decisions based on their expected income on the futures and spot market. However, if the underlying market design contains a capacity market or strategic reserves, then the assessment of investments is carried out considering incomes from the capacity remuneration as well. Section 7.5 focuses on the results, especially on the question whether the EOM can provide sufficient investments and guarantee generation adequacy. Parameters that are essential to improve the effectiveness of the EOM are also highlighted. Furthermore, it is described how much capacity remuneration mechanisms can improve generation adequacy ant to which costs. Finally, the main conclusions drawn from the results are summarized in the last section that also critically reflects on the applied modeling approach and discusses possible improvements going forward.

7.1 Literature review about security of supply and market design analyses

There is a wide range of research covering the issue of market design analysis and security of supply. Some of the literature follows a rather theoretical approach (e.g., Batlle and Rodilla, 2010; Cramton and Stoft, 2005; Stoft, 2002). However, few have conducted a model-based analysis that quantifies the effect of capacity mechanisms on electricity system and prices (Cepeda and Finon, 2011; Genoese and Fichtner, 2012; Vázquez et al., 2002).

Stoft (2002) states that price spikes are necessary for ensuring generation adequacy. These price spikes are required to cover all fixed costs of the generation capacities. Theoretically, a capacity market is not needed, but real markets have two failures: the mostly inelastic demand due to missing real-time metering, and the impossibility of excluding consumers not willing to pay for security of supply. Thus, capacity markets are necessary to encourage sufficient investment in new capacity. Cramton and Stoft (2005) argue that a capacity market is needed in most restructured electricity markets, and present a design that avoids the many problems found in the early capacity markets. They propose a capacity market, which induces supply to invest in sufficient generation that is in the right location, satisfies a reliability standard at low costs and is of the right type. They state that the market structure is imperfectly competitive, especially during times of peak load.

Genoese et al. (2012) use the agent-based model PowerACE to compare the impact of capacity payments (similar to that in the Spanish market) on electricity prices and new investments. The results show that a system with fixed capacity payments suffers from overcapacity and lower spot prices. The capacity payments overcompensate the lower electricity prices spot market.

With regards to security of supply, there are several studies that have been carried out recently. The Pentalateral Energy Forum (framework for regional cooperation in Central Western Europe) has published an analysis of the European electricity system until 2021 (Pentalateral Energy Forum, 2015) in which they have stated that there still will be enough capacity in the German market[1] by applying a Monte-Carlo simulation of a cost-minimizing dispatch model. In contrast, Borggrefe et al. (2015) conclude that there could be a capacity deficit between 2018 and 2022 in Germany, France, and Poland. The difference between these approaches is the input data: Whereas Pentalateral Energy Forum (2015) assumes significant investments in new capacity, Borggrefe et al. (2015) only consider projects, which are already in a more advanced stage, i.e., at least under construction.

[1] The calculated load serving probability for Germany, Austria, Netherlands, Switzerland is 100 %. Loss of load is only expected for Belgium and France.

7.1.1 The German discussion about market design options

Several studies focusing the German and European market have been carried out to analyze different design options. Frontier Economics (2014) and R2B (2014) concluded that an EOM is sufficient to ensure generation adequacy. The authors argue that there is still overcapacity in the European market, as the continuously improving European grid extension balances both renewable and load at different locations. Öko-Institut (2015) argues that the assumed DSM potential in these two studies is relatively optimistic. Moreover, by using a perfect foresight approach as done in these studies, it is not possible to reliably determine generation adequacy, as in practice investors face considerable uncertainty about the development of price peaks.

Agora Energiewende (2014) addresses the market power problem in EOMs. It argues that price spikes can theoretically cover fixed costs; however, they can only arise in a non-competitive market environment. The risk is that such situations occur too often, and the price level will become too high in an EOM. Also, it is argued that the electricity market is not a contestable market due to barriers such as sunk costs and long lead times. It concludes that an EOM is an interesting, but also a very hazardous game. Weber et al. (2014) claim in their study that the risks due to price volatility in an EOM can be very high, as the demand is very price inelastic and power plants need long construction time. Therefore, they regard a capacity market as more advantageous in the long term.

An analysis from Praktiknjo and Erdmann (2016) indicates that under the current market design, investments in new flexible capacities are economically unviable and the long run supply security could be in danger. EWI (2012) states that specific attributes of liberalized energy markets permanently challenge the security of supply. Therefore, it suggests the implementation of a market for security of supply contracts. Furthermore, the implementation of a strategic reserve is dissuaded as inefficiencies in the dispatch can occur, causing power plants in the reserve to be requested more often than necessary. A study about international experiences in capacity remuneration mechanisms in the context of supply security and cost efficiency has been carried out by Beckers et al. (2012). They claim that a strategic reserve is an effective option for short-term problems in supply security, but it is not necessarily price efficient. Notably, an EOM with a strategic reserve raises the question of sufficient investments into new power plants. Thus, Beckers et al. (2012) suggest establishing a capacity market, e.g., central or decentralized, but not a focused one.

7.1.2 Research gap in market design analysis

The literature review shows that there are plenty of studies on the theoretical aspects of the necessity of capacity markets. There are also some quantitative studies using mainly energy system models based on overall cost minimizing and focusing on the system view of design options. However, these studies do not take into account the behavior of investors with regard to different design options for the electricity market. Furthermore, existing quantitative approaches mainly use optimization models with perfect foresight that do not adequately reflect investment uncertainties. Investment uncertainties and imperfect market view of investors could hinder new power plant investments. Hence, these factors have a substantial impact on the security of supply, especially on generation adequacy, and have to be adequately captured within model analyses.

Therefore, to the best knowledge of the authors, an agent-based modeling approach has been developed and applied to analyze the market design for the first time. With the help of this approach, investments under different market design options (EOM, strategic reserve, capacity market) are evaluated. The decisions of single market participants (e.g., power plant operators) will be incorporated into the approach as market agents behavior. In contrast to optimizing system models, this approach considers investment decisions based on limited foresight and imperfect market information of agents in the electricity market. However, before the modeling approach for the EOM and other market designs is introduced in Section 7.3, the design options proposed for the German electricity market are described in detail below.

7.2 Market design options for the German energy market

With growing concerns that the EOM could not give sufficient incentives for investments in flexible power plants, several proposals are made for an alternative design of the electricity market, besides smaller changes to the existing EOM. The federal ministry already decided to introduce a capacity reserve in its proposal for the new electricity market act (see BMWi, 2018c). Table 7.1 summarizes all discussed proposals in Germany. Before analyzing selected approaches, the discussed proposals are described in the following section.

7.2.1 Strategic reserve

A strategic reserve can be designed in different forms but typically consists of several power plants that do not regularly participate in the electricity market. These power plants are still operated by their respective owners but are exclusively dispatched by the TSO, usually in extreme situations when the market price is close to the so-called VoLL[2]. The size of the strategic reserve is determined by the regulator whereas the price is settled in the market. The capacity is usually procured via uniform price auctions or bilateral contracts. By lowering the available capacities in the electricity market via the strategic reserve, market prices should increase, which in turn should incentivize new investments.[3] Over time, the available capacities in the market should reach a similar level as before, except for the inclusion of an additional reserve (Vries, 2007).

[2] The exact VoLL is difficult to determine and in practice a different value, e.g., the maximum allowed market price, might be used.

[3] In case of significant surplus capacities, the effect of the reserve on market prices will be negligible.

Table 7.1 | Proposed capacity mechanisms. The capacity mechanisms for the German electricity market differ in terms of the level of regulation, the technologies eligible for participation and the remuneration of contracted capacities.

Mechanism	Characteristics
Strategic reserve (BMWi, 2015; R2B, 2014)	• Central procurement of strategic reserve by TSO (about 5 % of the peak load) • Usage only if market does not clear • No way back for power plants
Central capacity market (EWI, 2012; Frontier Economics, 2014)	• Secured power plant capacity is prequalified • Regulator determines demand for capacity • RES receive capacity credits according to their availability
Decentralized capacity market (VKU, 2013)	• Decentralized procurement of capacity certificates by supply companies • Penalty for missing certificates
Focused capacity market (Öko-Institut, 2012)	• Only selected technologies are allowed to participate • Distinguish payment duration for existing and new power plants

One of the advantages of a strategic reserve is that it is easy to implement as well as to adapt to changing market conditions. Also, the impact on existing markets should be marginal. However, a strategic reserve also has certain drawbacks, one of them is the inefficient dispatch under normal market conditions, as the capacity in the strategic reserve is withheld from the regular electricity market. Determining the optimal volume of the strategic reserve is difficult because the available future capacity is subject to uncertainty. Moreover, the price at which the strategic reserve bids into the market needs to be determined carefully, as a lower price can reduce scarcity rents and lead to fewer investments (Cramton et al., 2013). Furthermore, a strategic reserve does not reduce investment related risks, such as price volatility, or address the missing money problem.

In Europe, several countries have already established a strategic reserve, namely Belgium, Finland, Poland, and Sweden (see Table 7.7 in the appendix). Sweden implemented a strategic reserve in 2011 but already announced that this reserve will be phased-out by 2020. The size of the strategic reserve in Sweden is currently around 1.50 GW. The costs in 2011 amounted up to 10.2 million Euros (Ministry of Enterprise, Energy and Communications Sweden, 2012). Similar to Sweden, Finland introduced a strategic reserve in 2011 with an initial capacity of 600 MW. However, in 2013 the capacity was reduced to 365 MW (Energy Market Authority, 2014). Belgium also established a strategic reserve in 2014 with a capacity of 850 MW. However, in winter of 2014, the unexpected unavailability of three nuclear power plants (Doel 3, Doel 4, and Tihange 2) caused scarcity in the Belgium market. If the unavailability of the three nuclear power plants were known beforehand, the tendered capacity would have been at least 2.10 GW. Yet, no loss of load occurred due to the mild winter even though forecasts expected scarcity situations (Elia, 2014). In Poland, according to the TSO, the required capacity of a strategic reserve ranges from 800 to 1000 MW. For the period between 2016 to 2018, a volume of 830 MW has been already procured, with an option to extend until 2020 (Polish Transmission System Operator [PSE], 2014). In comparison to other European reserves, the currently proposed volume of the strategic reserve for the German market[4] is relatively large (about 5 GW), but to put things into perspective, the German market is also larger than the markets in the above-mentioned countries. The strategic reserve is only dispatched at the maximum market price and hence does not affect scarcity prices.

[4] In the German context the proposed strategic reserve is referred to as "Kapazitäsreserve" (capacity reserve).

7.2.2 Central capacity market

In a capacity market, derivatives of generation capacity are traded between power generators and load-serving entities (LSE) or large consumers to ensure generation adequacy in times of shortages. EWI (2012) suggests a so-called market for security of supply contracts for the German electricity market. In such a market, a central instance contracts a certain level of capacity (see Figure 7.1), acting on behalf of LSES and large consumers, in order to guarantee power supply even in times of peak load. The central instance estimates the total peak load, and purchases secured capacity from the power plant operators based on estimated peak load plus an additional reserve margin (Target). Depending on the contracted and target capacity the height of capacity payments, e.g., between 0.5 and 2 CONE is set. In the EWI (2012) proposal, the available secured capacity is partially procured in an auction 5 to 7 years ahead in order to enable operators to offer units that are planned but have not yet been built.

The demand for conventional power plant capacity depends on the calculated reserve margin and the assessment of the regulator regarding how much power will be certainly generated from fluctuating RES. The rate at which the RES contributes to the secured available capacity is called capacity credit. In Germany, for example in the case of PV, a capacity credit of 1 % is suggested, because of the comparatively low generation during evening peak load hours in the winter months.

The auction of the comprehensive capacity market is organized as a "descending clock auction" also referred to as "Dutch auction" (see Figure 7.2). The starting value of the auction is set to twice the annuity of the investment costs for the cheapest, newly built conventional power plant, i.e., the CONE. The auctioneer announces this first price and calls for supply bids. Usually, the high starting price leads to oversupply, i.e., the volume of supply bids exceeds the capacity demand determined by the regulator. In the next round, the auctioneer lowers the price and requests new bids. If an oversupply occurs again, the auctioneer calls for the next round and repeats this procedure until the cumulated capacity from the supply bids equals the

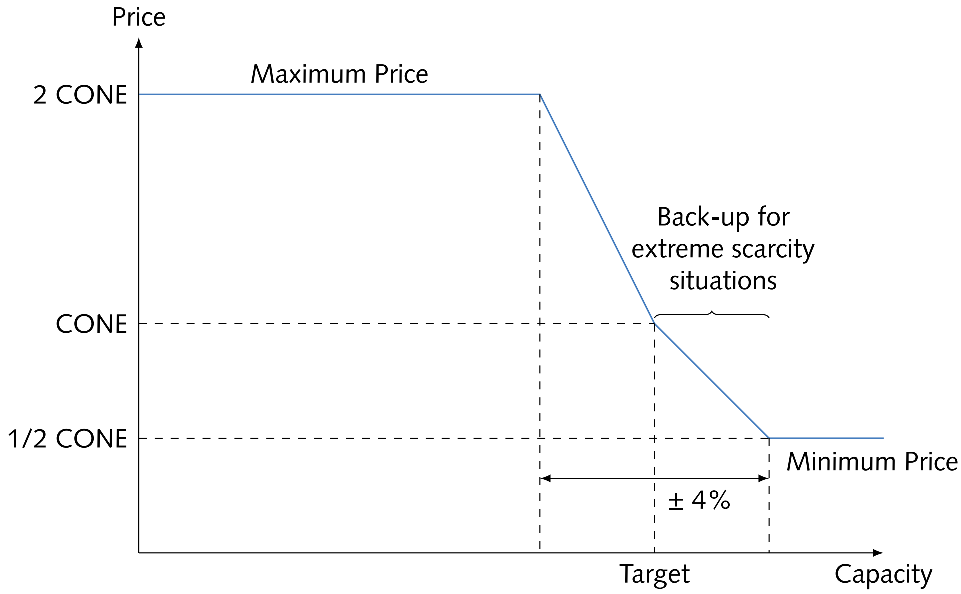

Figure 7.1 | Capacity demand curve. To be more robust against market power, the demand curve should be elastic near the targeted capacity level and, ideally, reflects the marginal value of firm energy. Source: Cramton and Ockenfels (2012).

demand capacity. Another criterion to stop the auction is the floor price. If the price is lowered after several rounds to the floor price by the auctioneer, the auction is stopped, and the floor price is announced at the settlement/capacity price. The capacity in the last round will be chosen as the capacity to be delivered from the suppliers. Existing plants receive the resultant capacity price from the auction for one year; new plants, however, can secure the capacity price for several years in order to decrease the investment-related risks.

Within a market design with a capacity market, investment decisions are based on the earnings from spot and derivatives markets as well as additional revenues on the capacity or control reserve markets. The mechanism with capacity options also protects consumers against high price peaks and represents another incentive for power generators to be available.

Besides the contracting of secured generation capacity, there is also the concept

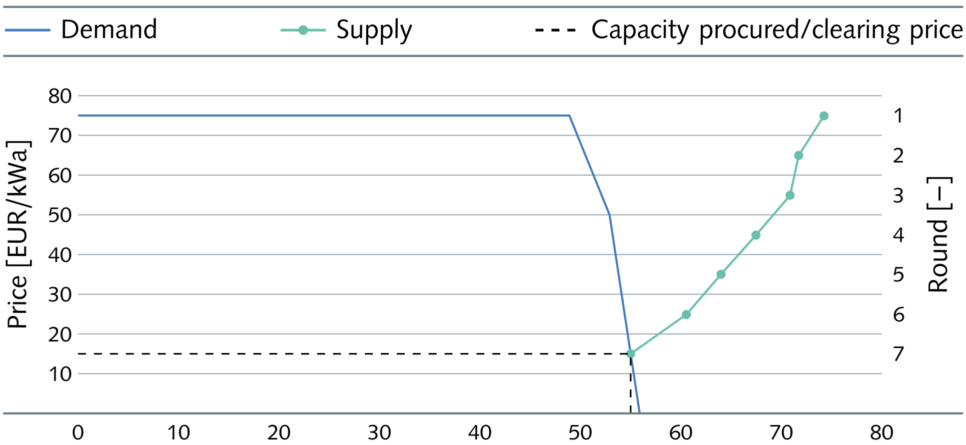

Figure 7.2 | Descending clock auction. In this schematic illustration of a descending clock auction, it can be observed how the supply of electricity generators and the demand of the regulator converge. The oversupply in the first round of almost 20 GW is gradually reduced, and completely eliminated in the seventh round, resulting in a clearing price of 15 EUR/kWa and contracted capacities of 55 GW.

of capacity options. In this case, the plant operators get an option premium for guaranteeing the availability of capacity on the electricity market. Moreover, if the performing price, e.g., the spot market price, exceeds a determined value (strike price) the seller of the option (the power plant operator) has to pay back the difference between strike price and performing price to the option holder, e.g., the system operator, even if the power plant does not generate any electricity or revenues. This equates to a penalty charge due to non-availability. Thus, exercising market power can be avoided considerably. The difference that has to be paid makes retention of capacity unattractive also to dominant power plant operators. However, the primary objective of this capacity mechanism is to ensure the availability of power plants, particularly in times of shortage (ISO New England, 2009).

7.2.3 Decentralized capacity market

The decentralized capacity market was introduced and proposed in a report by the VKU (2013). It is a type of comprehensive capacity market, in which operators of existing or new power plants and non-volatile RES act as providers of power certificates. Without any combination of other technologie, e.g., storages, only a very limited percentage of fluctuating RES nominal capacity can be offered as secured capacity.

In contrast to the central capacity market (see Section 7.2.2), the price and the demand for power certificates are determined based on the demand and supply of individual actors, not through a centralized planner. The regulator or a central instance certifies generation capacities and is therefore only responsible for the emission of the power certificates. However, the regulator determines neither the price nor the number of certificates that should be purchased.

Therefore, LSE and distributors (on behalf of their customers) as well as major industrial consumers determine their peak demand and purchase power certificates independently on the market. They can apply an additional product differentiation regarding flexible and non-flexible demand, and if necessary, purchase power certificates for the non-flexible part of the demand. Electricity consumers are then able to decide, whether they want to be fully supplied (and pay for certificates) or cut demand in times of shortages. This would allow charging costs for withholding capacity to the consumers. If consumers require more electricity in times of shortages than covered by certificates, they will incur a penalty charge. The penalty should be a multiple of the certificate price needed to motivate the entities to purchase a sufficient amount of certificates (BDEW et al., 2013).

7.2.4 Focused/selective capacity market

Focused or selective capacity markets incentivize predefined generation technologies. In contrast, comprehensive capacity markets support equally all technologies that are able to securely provide electrical energy to the system. In a proposal for a new energy market design, Öko-Institut (2012) suggest a differentiation between the remuneration of existing and new power plants. The rationale here is to switch a plant portfolio into a structure that supports the electricity system optimally. Regarding the German market with high impacts of fluctuating RES, this would lead to incentives for investments in flexible and storage technologies. To reach this target, it is possible to vary the number of payments or the amount of the payment duration. Hence, existing plants will receive lower payments or payments for a shorter period, whereas new plants or plants with the required attributes will receive higher payments for a duration up to several years.

7.3 Modeling energy-only markets and capacity mechanisms

To analyze the impact of different capacity remuneration mechanisms on the electricity market, different types of electricity market models can be used.

Ventosa et al. (2005) identified three main types of energy market models: optimization, equilibrium, and simulation models. Optimization models are able to find a cost-minimal or profit-maximal solution for an entire energy system from the perspective of one central planner. They are formulated as an optimization program by mathematical equations with (at least) one object function subject to technical and economic constraints. However, they do not integrate the view of individual market players. Market equilibrium models can consider the market perspectives: competition between all participants as well as the different market behavior of several participants. However, these models are difficult to use when the problem is highly complex. Finally, for modeling highly complex problems especially agent-based simulation models represent an appropriate approach. In general, they provide flexible frameworks to integrate different markets, such as day-ahead or capacity markets, and key market players (as agents) that pursue individual strategies (Tesfatsion, 2002). In order to address market problems, each agent can receive varying of information, along with various technical or economic restrictions such as their budget limitations or feasibility calculations. Furthermore, agent-based models can incorporate the behavior of investors with regard to different design options. In contrast to other approaches, agent-based models can adequately reflect investment uncertainties. As investment uncertainties and imperfect market view of investors could make investments in new power plant challenging, they should be considered within the security of supply and market design analyses. That is why agent-based models are well suited for modeling and analyzing of investments with regard to different design options for electricity markets.

7.3.1 Agent-based model for the electricity market

In the context of this chapter, an existing agent-based simulation model, which has already been applied to various electricity-market research questions, e.g., in Sensfuß et al. (2008) or Bublitz et al. (2014b), is extended by different capacity remuneration mechanisms. The model includes the key decision makers (generation companies, TSOs, regulator) and the most relevant market segments, e.g., the day-ahead market and the futures market. The generation companies are represented by agents that determine the short-term power plant dispatch and the long-term capacity extension. Therefore, interactions and feedback loops between short and long-term strategies can be analyzed. In addition, the model features an hourly time resolution. Thus, rare situations that only occur under the combination of special circumstances, e.g., high demand, low availability from RES and DSM, can be examined.[5] An overview

[5] However, implementing an hourly time resolution has the disadvantage of increasing the computational runtime, which takes up to two hours on a state-of-the-art workstation.

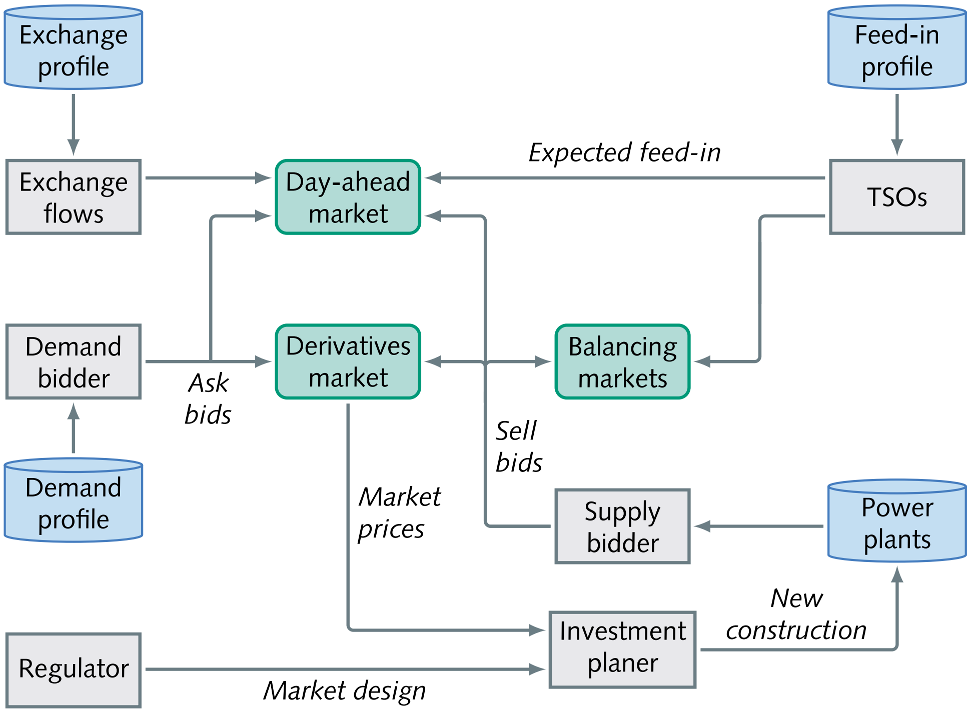

Figure 7.3 | The main elements of the agent-based model. This simplified diagram describes the connections between the individual agents and markets at the center of the model. In particular, the various supply bidders play an exposed role, as they participate in all markets and, thus, have a significant influence not only on the resulting prices but also on the investments made.

of the main elements of the model and the different interactions between the agents is depicted in Figure 7.3. A more in-depth description of the model can be found in Genoese (2010).

For the analysis in this chapter, the modeling of the day-ahead market and the investment decisions is of central importance and is described below.

Simulation of the day-ahead market

The day-ahead market is simulated in detail: Before the market clearing is carried out, all agents prepare their ask and supply bids. Bids for electricity generated from RES are sent by the TSOs to the spot market.[6] The calculation of the bid price for the supply bids is based on the variable costs $c^{\text{var}}_{a,h,j}$ of each power plant j, which include the costs for fuel, carbon emission allowances, and operation and maintenance:

$$c^{\text{var}}_{a,h,j} = \frac{p^{\text{fuel}}_{a,h,j}}{\eta_j} + \frac{\text{EF}_j}{\eta_j} \cdot p^{\text{cer}}_{d} + c^{\text{other}}_{j} \tag{7.1}$$

where

$p^{\text{fuel}}_{a,h,j}$: Fuel price in hour h of year a for power plant j

$p^{\text{cer}}_{a,h}$: Carbon emissions allowances price in hour h of year a

c^{other}_{j}: operation and maintenance costs of power plant j

EF_j: Emission factor of power plant j

η_j: Efficiency of power plant j

In order to adequately include the start-up costs, each agent forecasts the hourly day-ahead market prices of the next day d and estimates the operating hours of his power plants. If for a power plant j the variable costs are lower than forecasted hourly price, the agent assumes that this power plant will be in the market. Then, the agent calculates the expected start-up costs $c^{\text{start}}_{a,h,j}$ for each power plant:

$$c^{\text{start}}_{a,h,j} = r_j \cdot \left(p^{\text{fuel}}_{a,h,j} + \text{EF}_j \cdot p^{\text{cer}}_{a,h}\right) + d_j \tag{7.2}$$

where

d_j: Deprecation factor of power plant j

[6] This is a simplification of RES electricity sales to the wholesale market, as in reality large RES suppliers directly sell their RES electricity.

r_j: Ramping factor of power plant j

For each hour h in a period H where a power plant is expected to be continuously in the market, the agent submits a bid $b_{h,j}$ to the market operator that includes the start-up costs, the variable costs and a mark-up factor markup $m_{h,j}$ that depends on the market scarcity:

$$b_{h,j} = c^{\text{var}}_{a,h,j} + \frac{c^{\text{start}}_{a,h,j}}{|H|} + m_{h,j} \tag{7.3}$$

For each hour of the next day, the market operator cumulates the ask bids and the supply bids. These bids are compiled to generate the total demand and supply curve. The intersection between both curves equals the market clearing price and volume. Based on information about the accepted bids, the suppliers determine their power plant dispatch. Later DSM agents schedule their shiftable and sheddable loads.

Modeling of investment decisions

Once a year, all supply agents have the opportunity to extend their power plant portfolio. The investment decisions are part of an iterative process, in which the decision of one agent subsequently influences the decisions of the other agents. In order to avoid a preferential treatment to a particular agent, the order of the agents in the investment process is randomized each time. The process is stopped after each agent has evaluated his investment options by calculating the expected cash flows. The investment options, which are exogenously given to the agents, change over time and can differ for each agent, e.g., only agents who already own lignite-fired power plants can invest in new lignite capacities.

In order to estimate the short-term and medium-term cash flows from year a_0 to a_n, the agent regards hourly market prices $p^{\text{market}}_{a,h}$. Additionally, hourly forecast prices $p^{\text{fore}}_{a,h}$ are used in the calculation of the long-term cash flows applying a merit-order model that takes into account, among others, the expected capacity investments and demand:

$$p_{a,h} = \begin{cases} p_{a,h}^{\text{market}} & a_0 \leq a \leq a_n \\ p_{a,h}^{\text{fore}} & a > a_n \end{cases} \tag{7.4}$$

One of the major difficulties is the long-term prediction of prices, which rely on different uncertainties, such as future investment decisions of the agents. To incorporate future investments of other agents and their impact on cash-flows into the decision of an agent, the investment process could be reiterated in each time step[7] until a stable outcome is found for the investment decisions. In this equilibrium state, the agents are not willing to change their investment strategy, as no agent benefits from deviating. Taking into account the hourly time resolution for market simulation, the yearly time resolution for investments, the model horizon of several decades, and the numerous decisions of the agents, the resulting problem would be very computation-intensive. Therefore, a simplified approach is used where the first agent considers only the information on investments and decommissions available at the time of his decision. However, the next agent receives information about the investment decision made by the previous agent. If the next agent decides to construct an extra power plant, it is likely that the first agent has overestimated the value of his investment, owing to the price impact of this new capacity. The simulation results show that this primarily affects extreme peak prices, which can be lower than the forecast of the first agent.

In order to avoid such an overestimation, a model-endogenous price limit $\hat{p}$ is introduced into the investment calculation of the agents, to prevent that a few overestimated price peaks from distorting the investment evaluation[8]. This price limit leads to lower deviations between expected and realized cash flows.

[7] Investment decisions are made annually, so that for each yearly decision point of time the process has to be iterated.

[8] The technical price limit at the EEX day-ahead market is 3000 EUR/MWh.

$$CM_{a,j} = \sum_{h=1}^{8760} \min\{\hat{p}, p_{a,h}\} - c^{\text{var}}_{a,h,j} \tag{7.5}$$

$CM_{a,j}$: Contribution margin in year a for technology option j

Based on the calculated cash flows for different investment options, the economic feasibility is evaluated based on the NPV. If there are investment options with a positive NPV, the agent decides to carry out the investment option with the highest NPV. Later, the agent continues with the evaluation the next investment option and can carry out further investments. However, a limitation on the investment volume in one period needs to be introduced without which the first agent would construct until further investments became economically unfeasible, and the other agents would have no options for feasible investments. This constraint prevents an agent from achieving a market-dominating position. It also takes into account the financial limitations of the energy suppliers. The limitation, therefore, allows the agents to invest only in as much is necessary to keep their market share of conventional capacity, so that they stop their investment activity even if it is still feasible.

$$\text{NPV}_j = -I_{0,j} + \underbrace{\sum_{t=1}^{n_j} \frac{CM_{t,j} - c^{\text{fix}}_j}{(1+i)^t}}_{\text{expected income}} \tag{7.6}$$

Where:

NPV_j: Net present value of technology option j

$I_{0,j}$: Investment expenses in t_0 for technology option j

c^{fix}_j: Fixed expenditure per year for technology option j

i: Discount rate

n_j: Investment horizon for asset j

After an agent has made its decisions, the other agents evaluate their investment options considering the information about the investments of the first agent. The process is then repeated for all other supply agents. Figure 7.4 illustrates the whole investment process.

7.3.2 Modeling capacity mechanisms

Although several capacity remuneration mechanisms are currently discussed for the German electricity market, the focus will be set on the modeling and evaluation of the strategic reserve and central capacity market. The strategic reserve is close to acceptance by the political authorities and is expected to be installed very soon. For the central capacity market, the proposals contain detailed parameterization options. Therefore, these approaches can be evaluated with a robust modeling approach and thus the analyses will concentrate on these options in the following.

Strategic Reserve

Once a year, the transmission system operators put out a tender for the strategic reserve via a uniform price auction. The total procured capacity equals to 5 GW (about 5 % of the current peak load). The upper price threshold is by the CONE (55.70 kEUR/MW)[9] and the lower threshold equal to the lowest yearly fixed costs among all available power plants. As the operation of the strategic reserve is determined on a daily basis, only power plants with a low cold start-up time (less than 10 hours) are eligible.

If a power plant is part of the strategic reserve, it is not allowed to participate in other markets even after the contract expires. Therefore, all costs of such a plant have to be earned in the strategic reserve. The generation companies submit a bid b for each eligible power plant j to the market operator of the strategic reserve based on fixed costs c^{fix} and opportunity costs c^{opp}:

[9] For this analysis, the CONE is set by a gas-turbine with the following characteristics: a specific investment of 400 EUR/kW, yearly fixed costs of 9 EUR/kWa, an investment horizon of 15 years and an interest rate of 8 %.

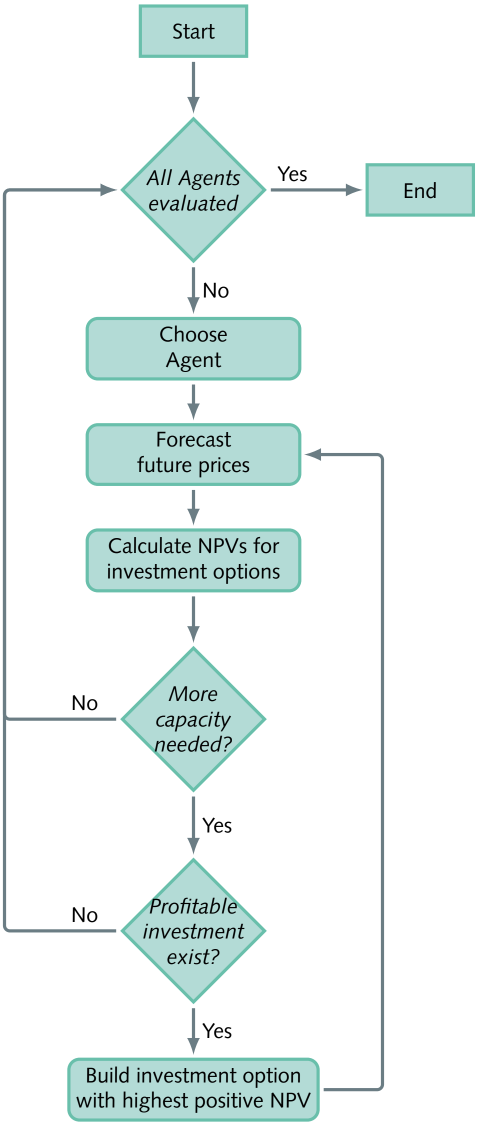

Figure 7.4 | Sequential diagram of the investment decisions process. In order to obtain the best-possible estimate, a new forecast is generated after each investment decision of each agent. In addition, to avoid excessive market power, the capacity expansion is limited per agent.

$$b_j = \max\{c_j^{\text{fix}},\, c_j^{\text{opp}}\}. \tag{7.7}$$

The opportunity costs are composed of the return from each market m and the option value of participating in other markets:

$$c_j^{\text{opp}} = \sum_m \text{return}_{m,j} + \text{option value}_{m,j} \tag{7.8}$$

As preliminary results show that mainly old power plants with only few remaining operation years enter the strategic reserve, the value is assumed to be zero in the analysis in Section 7.4.

Whereas the power plants, which are part of the strategic reserve, still belong to the generation companies, their dispatch is determined by the TSOs. The strategic reserve is only used in extreme cases, i.e., when the day-ahead market cannot be cleared. In these situations, the TSOs offer the total available capacity of the strategic reserve at the maximum day-ahead market price of 3000 EUR/MWh (EPEX SPOT, 2015). The accepted volume is then assigned to the different power plants of the strategic reserve based on a dispatch model that accounts for different technical restrictions. First, the plant with the lowest variable costs generates electricity, followed by the plant with the next lowest costs and so on. If a power plant is dispatched, the owner of the power plant is reimbursed for the occurring costs. Nevertheless, due to the large gap between variable costs and maximum market price, the TSO is able to retain at large share of the income thereby lowering the total yearly costs caused by the strategic reserve auction.

Central capacity market

The applied modeling approach follows the forward capacity market, which is currently being implemented in the ISO New England market area (ISO New England, 2009), and is comparable to the suggested design from EWI (2012).

As the first step, the regulator determines the amount of secured capacity and the reserve margin in year a to ensure a defined generation adequacy ratio. This is described by the equation:

$$ConCap_a = (1 + R_a)(D_{\text{peak},a} - RE_a - Imp_a) \tag{7.9}$$

Where:

$ConCap_a$: Required secured capacity in year a

R_a: Reserve margin in year a in [%]

$D_{\text{peak},a}$: Forecasted peak load in year a

RE: Secured available capacity of renewable generation plants in year a

Imp_a: Imports in the hour of peak load in year a

The reserve margin R can be chosen freely and controls the defined adequacy ratio. Next, the regulator determines the required capacity for each single LSE. This is accomplished by identifying the demand served by the particular LSE in the peak load hour. The capacity obligation of the respective LSE for the year a is then obtained by multiplying the values for $ConCap$ and the share of demand at the peak load time.

After determining the input parameters, the investment agents of the energy suppliers are asked for their respective bids. They can offer existing capacities (for a price of 0 EUR/kW) and new power plants (for a price within the floor and start price of the auction).

For the determination of the capacity price for new installations, the investment agents first estimate the NPV of the available technology options j. Subsequently, the offer price is determined for the option that has the highest NPV. The agents calculate the offer price based on Equation (7.10). The offer price is chosen so that the NPV becomes exactly 0 EUR/kW. New installations receive this calculated offer price for x years and a forecast price for all other y years in which they must participate in the capacity market.

$$\begin{aligned} \mathrm{NPV}_j = -I_{0,j} + & \underbrace{\sum_{t=1}^{n_j} \frac{CM_{t,j} - c_j^{\mathrm{fix}}}{(1+i)^t}}_{\text{expected income energy}} + \underbrace{p_{\mathrm{offer}}^{\mathrm{cap}} \sum_{t=1}^{x} \frac{1}{(1+i)^t}}_{\text{secured income capacity}} \\ & + \underbrace{p_{\mathrm{fore}}^{\mathrm{cap}} \sum_{t=x+1}^{y} \frac{1}{(1+i)^t}}_{\text{expected income capacity}} \overset{!}{=} 0 \end{aligned} \tag{7.10}$$

Where:

x: Period for fixed offer price

y: Overall capacity market participation period

$p_{\mathrm{offer}}^{\mathrm{cap}}$: Capacity offer price

$p_{\mathrm{fore}}^{\mathrm{cap}}$: Forecasted capacity price

After calculating the offer price, the investment agents submit the bids to the capacity market. The capacity auction is carried out as a descending clock auction (see Figure 7.2). Floor and starting price are determined by the regulator depending on the CONE. The capacity price should exactly cover the NetCONE at the optimum capacity. NetCONE corresponds to CONE minus the expected profits from the electricity markets. That can be explained as follows: When a peak load power plant generates electricity, all available power plants with lower marginal costs benefit from the uniform prices. A well-designed capacity market should, therefore, provide the

Table 7.2 | Investment options. The selected investment options are available to all, or in the case of lignite, only to specific agents. Over the years, the efficiency of the investment options continues to improves, but the costs and capacity remain the same.

	Size [MW]	Efficiency [%] 2015	2020	2030	Investment [EUR/kW]	Fixed costs [EUR/kWa]
Gas open cycle gas turbine (OCGT)	150	34	35	37	400	9
Lignite	1000	45	47	49	1700	42
Gas CCGT	800	56	58	60	800	18
Hard Coal	800	46	48	50	1300	34

precise fixed costs of a reference peak load power plant and could avoid a double compensation.

Finally, all bids are sorted in ascending order according to their offered capacity price, and the descending clock auction rounds are executed until the needed *ConCap* is reached. The final capacity price equals to that one at which demand and supplied capacity are equal. Whereas new plants receive this price for a longer period, all existing plants receive it for only one year.

7.3.3 Relevant model assumptions

Due to the in-depth representation of the German electricity market, detailed data is required for the model, which has been acquired from official public sources where available. For example, each power plant with a size greater than 5 MW is integrated based on BNetzA (2014). Historical hourly electricity feed-in of wind power and PV are taken from EEX (2015).

The model data, especially the one related to the future development of main energy market parameters, are derived from established energy scenarios. For instance, the development of carbon prices is based on market futures prices until 2020, after which the reference scenario of the European Energy Roadmap is used as the data source (European Commission, 2012). Fuel prices are based on (Sensfuß and Pfluger, 2014).

Table 7.3 | Central model assumptions. The model assumptions are based on publicly available data as European Energy Roadmap and in case no consistent data were available, the outcome of different energy system models was used. *Sources:* Elsland (2016); European Commission (2012); Sensfuß and Pfluger (2014).

	Unit	2020	2030	2040	2050
Coal prices	[EUR/MWh]	13.7	15.4	17.0	18.7
Gas prices	[EUR/MWh]	28.7	30.8	31.1	31.8
CO_2 Emission Allowances	[EUR/(t CO_2)]	7.3	23.5	47.9	51.0
Total annual demand	[TWh]	610.8	597.5	668.9	667.4
Export	[TWh]	53.8	15.8	–11.3	–15.4
PV	[GW]	47.5	47.4	80.7	80.7
Wind (onshore + offshore)	[GW]	47.9	60.8	81.7	104.8

The main power plant technologies modeled as investment options for the agents are listed in Table 7.2.

The input values of import and export flows, as well as the development path of renewable energies, are input data from an optimization model that calculates in advance the capacity expansion and power plant dispatch in all European countries based on the same assumptions for demand, carbon, and fuel prices. Germany continues to be a net exporter of electricity until 2030 due to the comparatively high penetration of renewable energies. After 2030, neighboring countries with lower costs of electricity generation from RES, increase their export of electricity and Germany switches from being a net exporter of electricity to a net importer.

The input values for PV and wind capacities are results from the applied optimization model (as it is for the export/import flows) of the European energy system. In the optimization model, the PV capacity is not expanded as long as the capex of PV is higher than the one of competitive technologies like wind power. This is why a further uptake of PV occurs only between 2030 and 2040 when the PV capex becomes competitive. The optimization model is applied without RES support after 2020 (see Sensfuß and Pfluger, 2014).

The development of the total annual demand is based on the assumption that energy efficiency measures will reduce energy demand in the next few years. This is already observable in the historical data for the total electricity demand in Germany between 2011 and 2015. However, due to an uptake of electric mobility in the long term, it is expected that electricity demand will increase from 2030 (see Table 7.3). The values for the demand development are calculated by the FORECAST model (Elsland, 2016).

DSM measures play a crucial role when evaluating the security of supply, as they can actively reduce the peak load demand. Therefore, different DSM technologies (Paulus and Borggrefe, 2011; R. D'hulst et al., 2015) are considered via hourly potentials. Two categories are distinguished: at first shiftable technologies, primarily from households such as washing machines or heat pumps with low activation costs, whose operation can be pre- or postponed by several hours (Gils, 2014; Klobasa, 2007; Klobasa and Ragwitz, 2006). Secondly, sheddable loads that mainly stem from different industrial processes, such as aluminum or chlorine electrolysis, but have higher activation costs, e.g., several hundred Euros, see Table 7.4. Due to the importance and the related uncertainty of the future development of DSM capacities, two scenarios are analyzed: a scenario with a moderate volume of available sheddable loads (EOM reference scenario) and one with an optimistic volume (EOM flexibility scenario).

7.4 Evaluation of market design options

The EOM and the other market designs, which provide a capacity remuneration mechanism, will be evaluated in the following section, especially focusing on their cost efficiency and ability to guarantee generation adequacy in the electricity sector. As it would be extensive to go into the details of all market design options, the analyses focus on the performance of the EOM, specifically the EOM extended with a strategic reserve and the central capacity market.

To evaluate their ability in terms of security of supply, an objective criterion is introduced to measure this ability. The first measure is the so-called adequacy ratio

Table 7.4 | Demand side management capacities. The shiftable capacity shows a constant growth over the years. In contrast, the sheddable capacity shows no significant development in both the low and high scenario. Furthermore, the activation costs remain the same over the entire considered period. *Sources:* (Gils, 2014; Gobmaier et al., 2012; Growitsch et al., 2013; Klobasa, 2007).

	Unit	2020	2030	2040	2050
Shiftable capacity	[GW]	5.56	6.66	8.46	12.53
Shiftable activation costs[a]	[EUR/MWh]		11–475		
Sheddable capacity (low)	[GW]	2.33	2.14	2.50	2.49
Sheddable capacity (high)	[GW]	7.56	6.44	7.41	7.39
Sheddable activation costs[a]	[EUR/MWh]		400–1300		

[a] The activation costs depend on the corresponding technology, e.g., a pulp grinding machine has activation costs of 11 EUR/MWh and a hot rolling mill possesses activation costs of 475 EUR/MWh.

AR, which is the minimum hourly ratio in each year y between available capacity AC and the residual demand RD in hour h:

$$\mathrm{AR}\,(y) = \min_{h \in y} \frac{\mathrm{AC}\,(h)}{\mathrm{RD}\,(h)} \tag{7.11}$$

However, as in the very extreme case of market failure—without enough available capacity meeting the demand—the withheld control reserve capacity contracted in the control reserve energy market would be used to avoid supply deficits and outages. The adjusted adequacy ratio AR′ is calculated adding the reserve capacity to the term of the available capacity:

$$\mathrm{AR}'\,(y) = \min_{h \in y} \frac{\mathrm{AC(h)} + \mathrm{reserves}\,(h)}{\mathrm{RD}\,(h)} \tag{7.12}$$

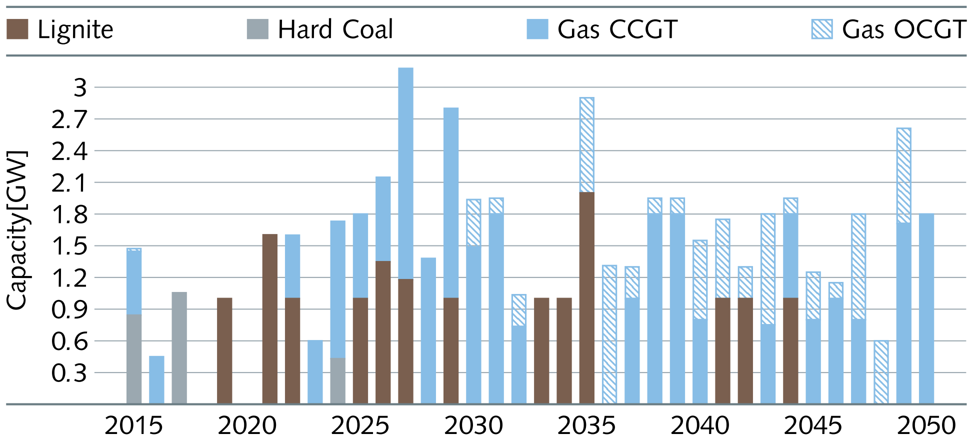

Figure 7.5 | Newly constructed capacities in reference scenario. In the beginning, lignite power plants are chosen as the most profitable investment. However, starting in 2021, investments in OCGTs and CCGTs are also favorable. With the rising carbon prices in mid-2030's, lignite-fired power plants are no longer being built and gas-fired power plants remain as an economically favorable technology.

7.4.1 Performance of the energy-only market in providing investment signals

Although the EOM is still able to stimulate investments in flexible power plant capacities in the model simulation, it seems that no market player in Germany is willing to invest in these capacities. However, if power plant capacity is getting scarce (the model results indicate this to be the case until 2023), electricity prices start to peak again, and the agents start to invest in different power plant capacities. Figure 7.5 shows that from 2021 on, the actors in the market start to invest again in power plants.Although a substantial reduction in the total capacity can be observed until 2023, the new investments lead to a more or less balanced amount of flexible capacities (in total about 70 GW) between 2023 and 2050 (see Figure 7.6).

A slow increase in the electricity demand is assumed in the model from mid-2020's (due to the growing market penetration of electric vehicles and other technologies relying on electricity). Therefore, the nearly constant level of flexible capacities does not mean that the demand can be met within the day-ahead spot market all the

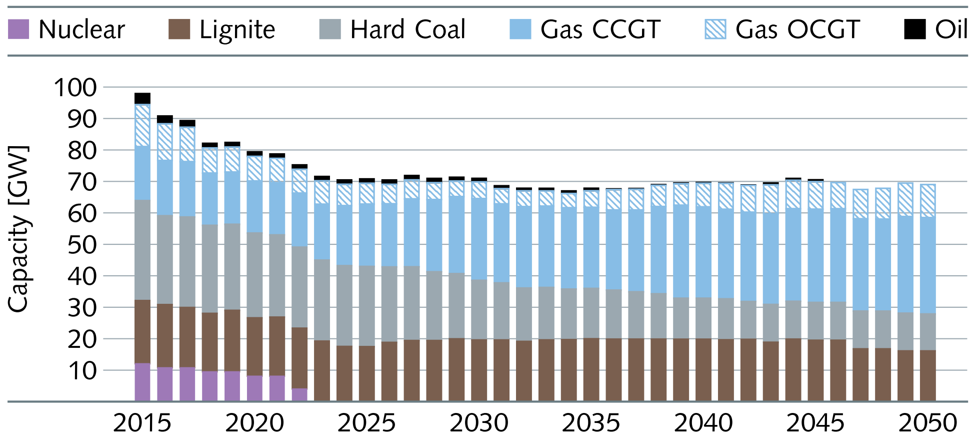

Figure 7.6 | Dispatchable capacities in the reference scenario. The capacity development shows that coal-fired power plants are steadily being replaced by CCGTs. However, lignite power plants remain highly profitable mainly due to the low fuel costs and only slightly increasing carbon certificate prices in the reference scenario.

time. Figure 7.7 depicts the development of the adequacy ratio for the EOM reference scenario with a moderate potential for sheddable loads of about 2.10 GW by 2050. An adequacy ratio above 1.0 means that the demand can be completely served by the supply capacity in each hour of the analyzed year. Moreover, an adequacy ratio under 1.0 means that the demand cannot be covered entirely with the capacities in the spot market at least in one hour. By this measure, brownouts which are not favored could be avoided. However, market clearing on the spot market can hardly be guaranteed without additional measures in several scenarios. Hence, without capacity mechanisms or the activation of higher potentials of sheddable load capacities, the generation adequacy cannot always be guaranteed by the EOM itself.

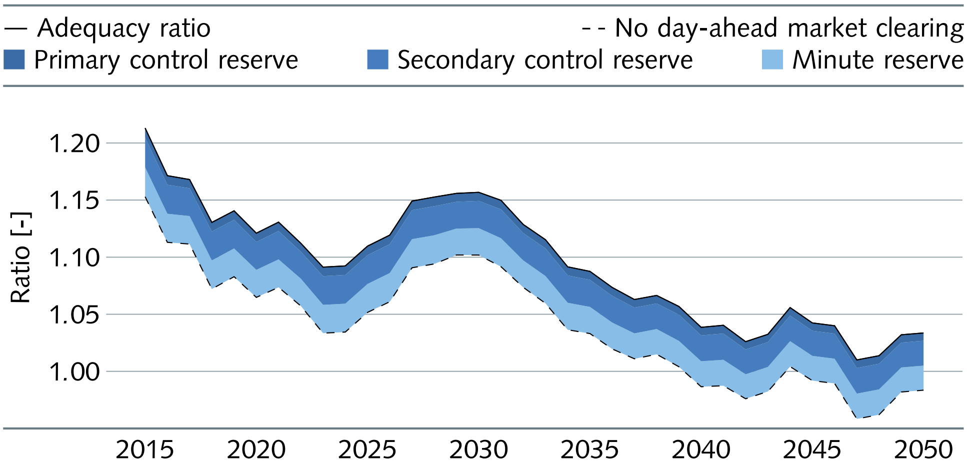

Figure 7.7 | Adequacy ratio in the reference scenario. Between 2030 and 2040, the adequacy ratio decreases steadily, although a market clearing is still feasible at all times. However, from 2040 onwards, control power is required in selected situations of each year in order to avoid an undersupply of the demand.

Influence of demand-side-management

As mentioned, the total volume of available sheddable loads is assumed as 2.10 GW in the EOM reference scenario, whereas the potential for the shiftable load is given in Table 7.4. To determine the impact of DSM and especially that of sheddable loads an additional scenario – the EOM flexibility scenario – is introduced for the analyses. In this scenario, a much higher available potential of sheddable loads is assumed (max. 7.6 GW), whereas the shiftable loads remain unchanged. The development of the adequacy ratio in the EOM flexibility scenario is significantly higher (see Figure 7.13 in the appendix) than in the reference scenario. This is why only in 2047 control reserve power is required to avoid an undersupply. In the years after 2047 market clearing can be guaranteed again. Thus, demand flexibility, particularly as sheddable loads, can make a significant contribution to the security of supply in future (Zimmermann et al., 2016).

Impact of a phase-out of lignite power plants

Furthermore, a scenario is analyzed in which new investments or retrofits of existing lignite capacity are prohibited by law. This scenario reflects the ongoing discussion about the lignite phase-out in Germany. The scenario results show that the development of total capacity in the market barely differs from the scenarios in which investments in lignite power plants are allowed. Decommissioned lignite and coal plants are mainly replaced by OCGT and CCGT plants. Although fewer investments are made in total, fewer power plants are shut down for economic reasons. As the total capacity remains nearly the same as in the scenario with lignite investments, there are only little differences in the development of the adequacy ratio (see Figure 7.15 in the appendix). Similar to the EOM reference scenario, the day-ahead market cannot be cleared from 2040 unless the available volume of sheddable loads cannot be increased drastically.

7.4.2 Enhancing security of supply via capacity remuneration mechanisms

After the strategic reserve is procured for the first time in 2015, it takes the generation companies several years to adapt completely. Afterwards, the overall capacity of thermal power plants is on average about 5 GW (equal to the total capacity of the contracted strategic reserve capacity) larger than in a scenario without a strategic reserve. Additional gas-fired peak load power plants are primarily built by the investment agents. This effectively increases the generation adequacy as shown in Figure 7.11 and prevents brownouts that may occur in simulations where capacity is not enumerated. The strategic reserve is dispatched for the first time in 2035 and a peak dispatch of more than 60 hours is reached in the following years (see Table 7.8 in the appendix). Further, in an ex-post consideration of stochastic outages the reserve is already dispatched in the 2020s. Nonetheless, the total capacity of the strategic reserve is never fully dispatched, and the maximum dispatch volume amounts to 4.3 GW (usually this volume is between 1 and 2 GW).

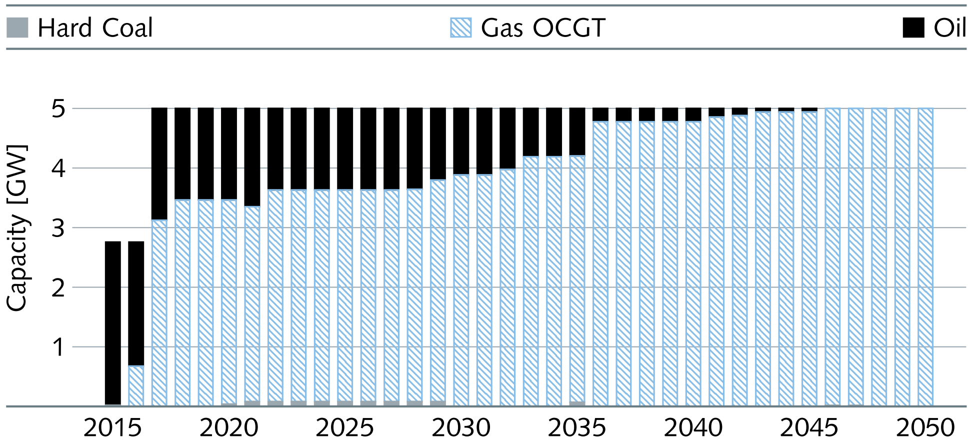

Figure 7.8 | Capacities in the strategic reserve. As the fixed costs represent a large percentage of the total costs of power plants in the strategic reserve, the reserve mainly consists of gas- or oil-fired peak load power plants with low fixed costs. Only a few old coal-fired plants, which are not competitive anymore due to their comparably low efficiency and low opportunity costs, become a part of the strategic reserve.

The capacities of the strategic reserve are dominated primarily by gas-fired power plants, which feature the lowest fixed costs compared to all other technologies (see Figure 7.8). Even though new power plants are eligible for the strategic reserve, they represent only a small share of the total capacity in the strategic reserve. This is because the new power plants, which directly enter the strategic reserve have to earn their fixed costs as well as their investment expenses, in contrast to an already existing power plant for which the investment expenses can be regarded as sunk costs.

The costs of the strategic reserve amount to nearly 5 billion EUR, which can be split up into about 3 billion EUR that are incurred before 2030 and about 2 billion EUR that are incurred between 2031 and 2050. Although the auction prices reach the price limit of the CONE after 2040 (see Figure 7.14 in the appendix), the total yearly costs of the strategic reserve are on average lower than before, which originates from high profits in hours in which the reserve has to be dispatched. Nevertheless, this result must be viewed with caution. For a holistic comparison, the results from other energy markets have to be taken into account as well. These can then lead to overall higher costs for the consumers compared to a capacity market.

The auction prices and the capacity surplus are interrelated. When a deficit is expected, power plants are more profitable in the regular markets. Therefore, the power plant owners bid higher prices to the strategic reserve auction, in some cases higher than the CONE. In case of surplus capacities, generating companies expect low profits from other markets and are therefore willing to accept low markups on their variable cost to cover the fix costs. In these years, the strategic reserve might not even be dispatched.

Central capacity market

Compared to the EOM, a central capacity market leads to a higher volume of power plant capacity, especially after 2025 (see Figure 7.6 and Figure 7.9). However, because of the reserve margin of 5 % and low capacity credits for RES, the development of installed conventional capacity seems to indicate overcapacities of thermal power plants. The simulation results show that reducing the reserve margin or increasing the capacity credits for renewable energies can significantly decrease the installed conventional capacity and vice versa.

New investments benefit from the capacity market. However as the CONE has a substantial impact on the bids in the capacity market, technology options with low investment expenses benefit from capacity cash flows and the investment agents invest in these options. The new investments are in most cases profitable. Considering that the German energy sector has a high capacity of fluctuating renewable energies and flexible usage of gas turbines, they are a preferred complement to the fluctuating generators to maintain a sufficient adequacy ratio (see Figure 7.10).

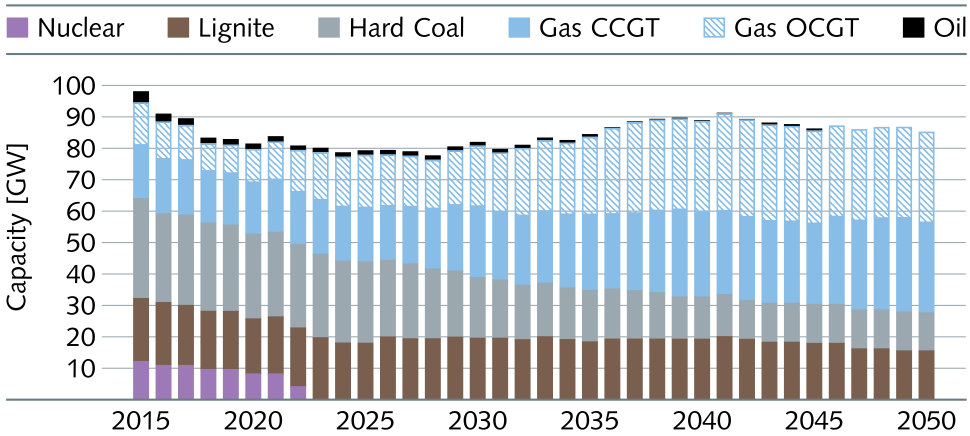

Figure 7.9 | Capacities in the capacity market scenario. The central capacity market leads to a high volume of power plant capacities, whereby the differences compared to the reference scenario are almost exclusively due to a higher investment in OCGTs. This is due to the fact that these additional power plants are rarely used or, in extreme cases, are not used at all and, therefore, their low fixed costs are decisive.

7.4.3 Comparison of the different design options

The adequacy ratio of the different market designs is shown in Figure 7.11. The shape of the adequacy ratio development in the scenario with a strategic reserve is similar to the one in the EOM reference scenario, the difference being that the capacity of the strategic reserve leads to a higher adequacy ratio. With high values of the reserve margin applied to the demand curve of the capacity market, there is always sufficient generation capacity available. This means that the probability of a black or brownout is lower than in other market design options. The loss of load expectation (LOLE)[10] is indeed zero in the capacity market design, whereas the LOLE is quite high after 2035 in the EOM design and EOM with a strategic reserve (see Table 7.9 in the appendix). Furthermore, the comparison of the different DSM scenarios (EOM reference and EOM

[10] The LOLE is calculated here without considering operating reserves. Although operating reserves might be used to avoid loss of load, its original role is balancing load fluctuations and grid failures. That is why in this case the definition of the LOLE is equal to the number of hours in which the spot market cannot be cleared.

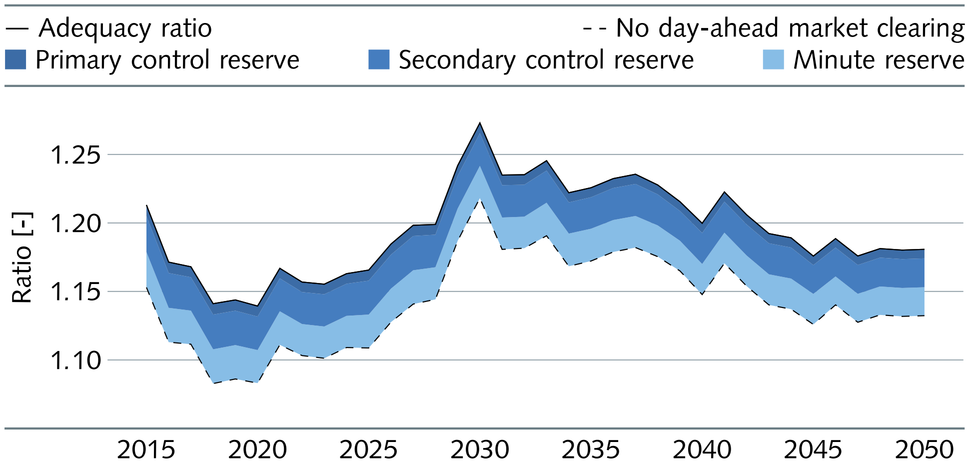

Figure 7.10 | Adequacy ratio in the capacity market scenario. With the defined capacity credits for RES, the adequacy ratio is continuously over 1.10, which indicates the existence of slight overcapacities and the necessity of a recalibration of the design parameters. The low value of the security factor at the beginning is mainly attributable to the fact that in particular the required base load power plants have long construction times and therefore do not have an immediate effect. However, as a result in the medium term, fewer peak load power plants are required and built.

flexibility) shows that the LOLE can be strongly reduced with the help of interruptible loads.

However, this high ratio does not necessarily lead to an (cost) efficient market design. No clear conclusion about the most efficient market design can be drawn due to existing uncertainties regarding the parameterization and regulatory decisions (Mastropietro et al., 2016). The average spot market price is considerably higher in the EOM and strategic reserve design than in a market design with a capacity market during scarcity periods (see Figure 7.12). However, as in the capacity market, payments are made to the electricity producers, it cannot directly be derived that the total costs of the capacity market design are actually lower.

Whereas the EOM needs price spikes to cover all fixed costs of power plants that are on the right side of the merit order, capacity markets generate additional payments to generators. Therefore, the average price is lower than in the EOM almost all of the

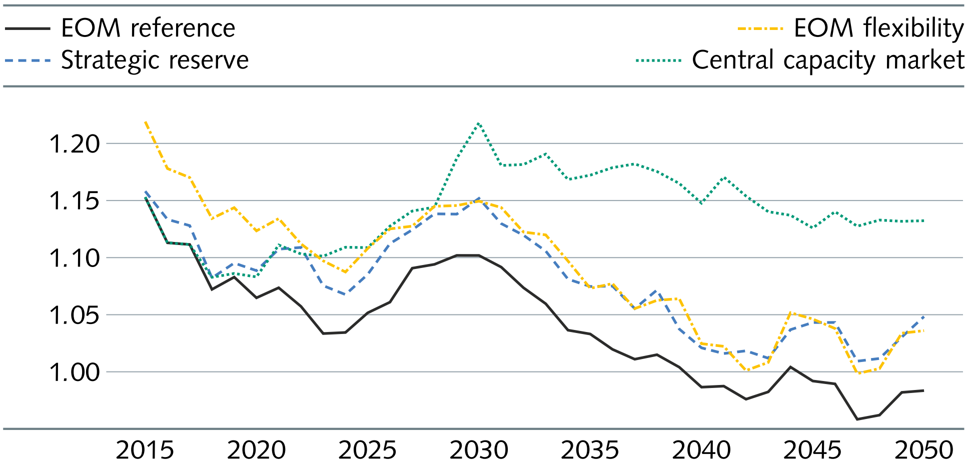

Figure 7.11 | Comparison of the adequacy ratios. The shape of the adequacy ratio development in the scenario with a strategic reserve is similar to the reference scenario. However, the difference remains that the capacity of the strategic reserve leads to a higher adequacy rate similar to the flexibility scenario, which, is approaching but does not fall below the critical value of 1 towards the end. If, however, a centralized capacity market is introduced, the adequacy ratio is continuously high, i.e., over 1.10 after 2022.

time. However, analyzing the total costs of thermal electricity generation, it can be observed that the cumulative costs by 2030 are lower in the EOM than in the market designs with a capacity mechanism. This cost advantage diminishes until 2050, and the cumulative costs with a capacity market are similar to the ones of the EOM (see Table 7.5).

Furthermore, the cost comparison shows that in an EOM, in which a higher level of DSM, especially sheddable loads with high activation prices, are available (EOM flexibility), the total costs for electricity generation (except funded RES) are lower than in the low DSM-scenario (EOM reference). This is due to the fact that the higher volume of DSM activation does not only ensures market clearing at scarcity times but also sets the price between 400 to 1000 EUR/MWh avoiding price settlement at $p_{\max}$ (3000 EUR/MWh in the day-ahead market). Hence, the total system expenses

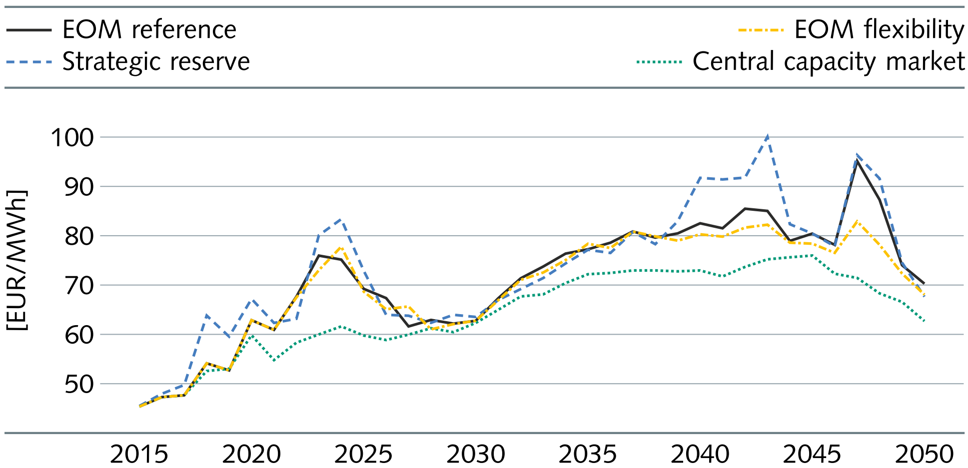

Figure 7.12 | Comparison of the average market clearing prices. With the exception of the capacity market, all prices show a similar pattern which is related to the fact that, in the capacity market, no scarcity signals are required to stimulate investment and a constant overcapacity is maintained. Therefore, no price spikes occur. However, the price difference is negligible in non-scarcity times, e.g., between 2027 and 2035.

are lowered by more than 20 billion EUR.[11]

7.5 Critical reflection and outlook

Although the entire German electricity market and various design options are modeled with a bottom-up agent-based approach, some limitations of the methodology remain. One of the limitations is that electricity exchange with the neighboring European electricity markets is incorporated with static export/import profiles. Hence, dynamic reactions from abroad to specific market situations in Germany are not regarded. In a dynamic approach, the available capacities from the neighboring countries may be different. Therefore, the next modeling steps should expand the described approach to a European market model that allows the simulation of different design

[11] The cost comparison does not consider investments that enable the availability of DSM. Therefore, the cost advantage can at least partly diminish due to investments in information and communication technology (ICT) or in other technologies required to activate more DSM potentials.

Table 7.5 | Cumulative payments to the generation companies under different market designs. The flexibility scenario has the lowest total values as additional flexibility is available, but its development is regarded as exogenous. Thus, possible investments are not included in numbers below. However, if only the second period from 2031 to 2050 is considered, a central capacity market is preferable, especially if few flexible capacities are available.

[Bn EUR]	EOM reference	EOM flexibility	Strategic reserve	Central capacity market
2015–2030	393.8	394.9	413.5	420.1
Capacity remuneration	–	–	2.9	61.6
Day-ahead market	393.8	394.9	410.6	358.5
2031–2050	479.1	457.8	494.6	454.1
Capacity remuneration	–	–	2.6	60.7
Day-ahead market	479.1	457.8	492.0	393.4
Total sum	873.0	852.8	908.2	874.2

options for European electricity markets. In this case, for example, the introduction of the French capacity market (which was recently installed) and its interaction with the German electricity market could be analyzed in detail. Besides, the exchange flows, the available DSM capacity is also incorporated as an exogenous variable. This approach does not enable the analysis of investments in DSM capacity considering capacity payments. Therefore, within future research investments in DSM capacity could be also endogenously modeled.

Furthermore, the existing study analyses only the development of the national capacities and the peak demand that has to be served. Thus, the generation adequacy question is answered only in general (without considering stochastic outages of power plants or grids). Moreover, possible bottlenecks for specific regions in the country are not taken into account by this approach. This is a reason to implement the transmission grid or at least the main transport restrictions into the introduced market model, which allow the analysis of the regional generation adequacy.

Finally, it is important to mention that some methodological improvements could be also done in future studies. The learning of agents could be rendered more precisely so that for example, agents are affected by their former misinvestments or by the ones of their competitors thereby making their decisions not only based on economic assessments, but also based on their soft skills.

All in all, it can be stated that with the existing modeling approach important analyses and conclusions could be derived regarding the effectiveness of the EOM and other market design options to incentivize investments in flexible power plant technologies and thus to guarantee generation adequacy.

7.6 Conclusions

The proposed application of agent-based modeling is an appropriate approach to investigate imperfect market conditions, as it incorporates the limited foresight of market players and enables to detection of possible electricity market failures in the future. The approach is used to analyze, whether the current market design in Germany is able to incentivize investments into power plants, so that generation adequacy is guaranteed, or if capacity remuneration mechanisms are needed.

The results indicate that the existing EOM leads to a market equilibrium in the short and medium term. The generation adequacy is ensured as adequacy ratio is always above 1.0, which means the supply side can deliver the required capacity in every hour to meet the electricity demand. However, this is a result of surplus capacities existing in the current German electricity market originating mainly from the period before liberalization and the coupling of European electricity markets. Furthermore, it is worth mentioning that these results also rely on the condition that at least a moderate level of sheddable loads (2 GW) can be activated during peak load hours.

In the long run (beyond 2030), the results show that generation adequacy cannot be fully guaranteed in the EOM. The demand cannot be completely met in several hours by the available capacity in the spot market, and at least spinning and non-spinning reserve power has to be dispatched in order to avoid brownouts. Due to uncertain cash flows and price peaks only occurring in a few hours, the agents do not make sufficient investments. The functionality of the EOM can be improved, if the available capacity of sheddable loads is increased to about 8 GW or if a capacity reserve with a capacity of 5 GW is implemented. Hence, the capacity reserve proposed by the Federal Ministry for Economics can provide long-term generation adequacy in Germany. Thereby, it can be derived from the results that this reserve mainly consists of existing lignite, gas and oil-fired power plants and rarely of newly built power plants. Apart from these findings about the EOM, it is shown that the ban on the construction of new or renewal of existing lignite capacities would not have a significant effect on the generation adequacy ratio in the EOM.[12]

Regarding DSM, sheddable loads can increase the generation adequacy also in the long term, as they set price peaks at several hundred EUR/MWh, which are necessary in the EOM to refinance investments. In contrast, shiftable loads with bidding prices between 11 to 475 EUR/MWh (Table II) do not set such high prices and even avoid price peaks, as they lead to a more balanced demand curve. A smooth demand curve means less peak load and therefore reduced or minimal price peaks. Missing price peaks, in turn, lower the profitability of power plants and can lead to fewer investments so that the availability of shiftable loads can improve the security of supply in the short term, but not in the long term. Furthermore, the shifted demand is not able to cause a considerably higher price level in off-peak hours due to a flat merit-order curve, which again does not improve the conditions for new investments.

The analysis of capacity remuneration mechanisms indicates that a central capacity market can ensure nearly constant investments during the whole period until 2050 without generating higher total system costs. The capacity payments are compensated by avoided price peaks, on which the EOM relies. It can be concluded that the capacity level in total is noticeably higher in the capacity market design than in the EOM. The

[12] This does not hold for a swift phase-out of lignite capacities.

highest investments are made in OCGTs followed by CCGTs. Based on the proposed capacity credits for renewable energy technologies, an adequacy ratio of more than 1.10 can be reached with the help of a capacity market. This means that a reserve capacity of at least 10 % is available during the whole period.

In summery, an EOM extended with a strategic reserve capacity of 5 GW can provide generation adequacy. The EOM can also guarantee generation adequacy if sheddable load potentials can be strongly activated. However, a pre-defined adequacy ratio can be more easily achieved with a capacity market. The main challenge of a capacity market remains the appropriate parameterization to avoid overcapacities (and related costs) and the adequate integration of RES technologies.

As the EOM can guarantee generation adequacy in the short and medium term without higher costs and does not require major political intervention, the authorities are recommended to keep the existing market design until the early 2020ies. However, in the middle of the next decade, the introduction of a comprehensive capacity market should be prepared and implemented. A strategic reserve seems to be more expensive in the long term. To increase the security of supply in the EOM, a strategic reserve can be an option for the next ten years; however, in the long run, a capacity market is more favorable.

Finally, it is worth mentioning that the introduction of capacity markets in the European electricity markets should be coordinated. In contrast to EOMs, capacity markets can slow down inner-European electricity trade and hinder the development of an integrated European market, especially if capacities are bounded locally.

7.7 Additional results

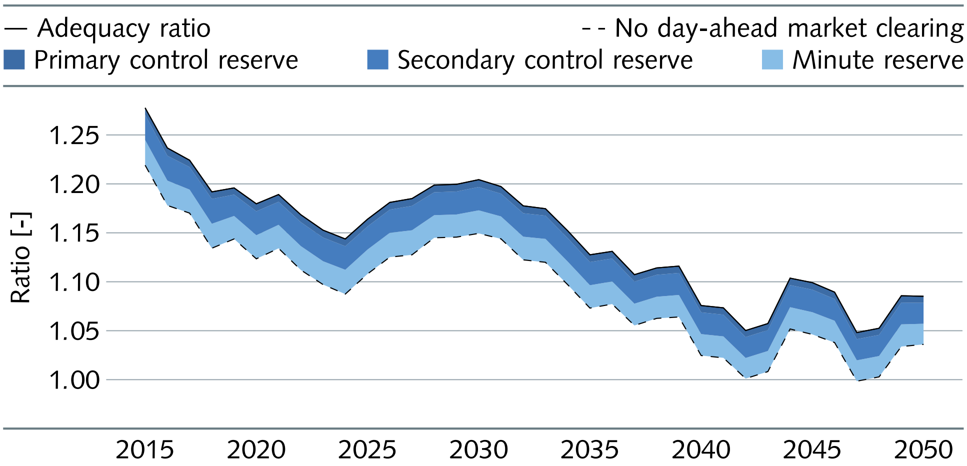

Figure 7.13 | Adequacy ratio in the flexibility scenario. Between 2030 and 2040, the adequacy ratio decreases steadily, but its value is still greater than 1.05. From 2040 the adequacy ratio stabilizes in the range of 1.00 to 1.05 and in 2047 control reserve power is required to avoid an undersupply.

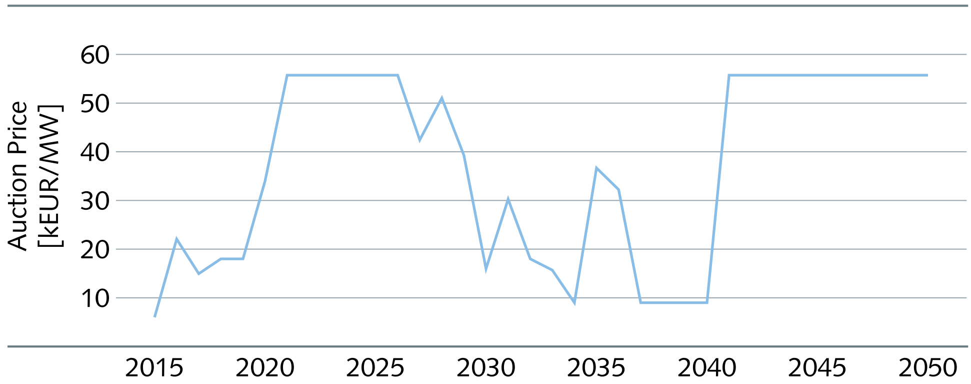

Figure 7.14 | Yearly auction prices for the strategic reserve. Annual capacity prices are highly volatile and are limited by the lowest fixed annual costs, here 9.0 kEUR/MW, and by the CONE of (55.7 kEUR/MW). The upper limit is reached mainly towards the end of the examined period of examination, where investors invest only to a small extent.

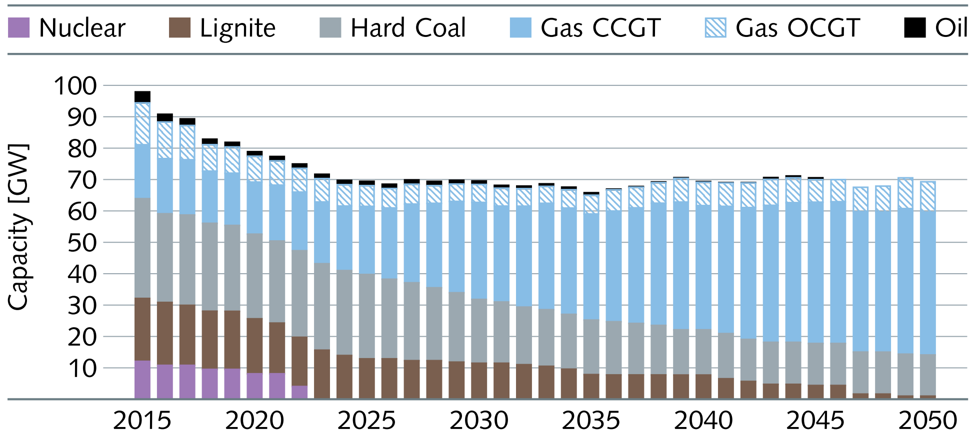

Figure 7.15 | Development of the conventional capacities with a lignite phase-out. In this phase-out scenario, the construction of additional lignite-fired power plants is prohibited, but existing plants may remain in operation. Compared to the reference scenario, lignite capacities are largely replaced by additional gas-fired power plants.

Table 7.6 | Goodness of fit for the linear regression model. Almost all coefficients of the selected fundamental variables are highly significant, except for the coefficients of the gas price for several hours on weekends and the coal price in some night hours on weekends. As the load is typically lower on weekends and during the night, gas-fired power plants usually do not run on weekends and thus, is it not surprising that the gas price is not affecting the electricity price. The same holds true for the coal price as during very low load situations only base load plants are operating.

	R^2		R^2 adj		RMSE	
Hour	WD	WE	WD	WE	WD	WE
0	0.767	0.745	0.766	0.741	4.502	5.915
1	0.740	0.744	0.739	0.740	4.683	5.753
2	0.726	0.723	0.724	0.719	4.960	5.981
3	0.711	0.716	0.710	0.712	5.078	5.991
4	0.724	0.699	0.722	0.694	4.743	6.237
5	0.770	0.703	0.769	0.698	4.916	6.444
6	0.695	0.712	0.693	0.708	6.010	6.811
7	0.712	0.746	0.710	0.742	6.054	6.479
8	0.739	0.772	0.738	0.768	6.192	6.326
9	0.784	0.788	0.783	0.785	6.080	6.197
10	0.793	0.801	0.791	0.798	6.129	6.163
11	0.817	0.798	0.816	0.794	5.838	6.296
12	0.829	0.798	0.828	0.795	5.570	6.119
13	0.838	0.785	0.837	0.782	5.314	6.063
14	0.834	0.764	0.832	0.760	5.005	5.965
15	0.815	0.755	0.814	0.751	4.941	5.852
16	0.788	0.758	0.787	0.754	5.125	5.851
17	0.770	0.767	0.768	0.763	5.611	5.914
18	0.714	0.771	0.712	0.767	7.074	6.145
19	0.690	0.763	0.688	0.759	6.962	5.977
20	0.741	0.794	0.739	0.791	5.306	5.025
21	0.741	0.822	0.739	0.819	4.860	4.657
22	0.791	0.790	0.789	0.787	4.349	4.923
23	0.800	0.751	0.799	0.747	4.152	5.643

Table 7.7 | Strategic reserves in selected European countries. The size of the strategic reserve depends on the peak load and is close to 5 percent in the countries listed in 2015. All values correspond to historical figures with the exception of Germany, where until now only plans for the implementation of a strategic reserve exist. *Source:* (ENTSO-E, 2018b).

Country	Peak load 2015 [GW]	Strategic reserve capacity [GW]	Percentage of peak load [%]
Belgium	13.13	0.85	6.47
Finland	13.58	0.60	4.42
Germany	77.50	5.00	6.45
Poland	23.07	0.83	3.60
Sweden	23.40	1.50	6.41

Table 7.8 | The dispatch of the strategic reserve. Starting in 2035, the strategic reserve with capacity of 5 GW is increasingly being used. However, considerable fluctuations occur over the years. Sometimes almost the entire reserve is used, sometimes only a small fraction.

Year	Number of hours [-]	Total usage [GWh]	Max. usage [GW]
2035	0	0.0	0.0
2036	0	0.0	0.0
2037	2	0.3	0.2
2038	0	0.0	0.0
2039	9	6.2	2.1
2040	36	42.9	3.2
2041	37	43.5	3.5
2042	35	43.5	3.4
2043	60	73.6	4.0
2044	11	8.7	1.7
2045	6	3.1	1.1
2046	6	3.8	1.1
2047	62	80.0	4.3
2048	54	63.8	4.1
2049	9	8.3	2.3
2050	2	1.0	0.9

Table 7.9 | Loss of load expectation. The LOLE varies widely from scenario to scenario. Only in case of the capacity market, sufficient capacity is available at all times. Interestingly, despite similar additional capacities, the LOLE is considerably lower in the flexibility scenario than in the scenario with a strategic reserve. This is related to the fact that higher prices occur at an earlier stage, thereby signaling shortage signals and incentivizing new investments.

year	EOM reference	EOM flexibility	Strategic reserve	Central capacity market
2035	0.6	0.0	6.2	0.0
2036	3.4	0.0	3.8	0.0
2037	15.6	0.0	14.6	0.0
2038	10.9	0.0	5.4	0.0
2039	21.8	0.0	17.1	0.0
2040	39.6	1.0	25.8	0.0
2041	40.0	1.4	25.2	0.0
2042	52.0	5.8	23.7	0.0
2043	46.7	5.2	27.6	0.0
2044	14.8	0.0	13.4	0.0
2045	22.5	0.1	10.4	0.0
2046	28.6	0.3	10.5	0.0
2047	79.4	17.6	26.4	0.0
2048	69.1	10.8	22.7	0.0
2049	29.7	0.6	12.5	0.0
2050	31.0	0.5	7.5	0.0

Chapter 8

Agent-based simulation of interconnected electricity markets

Today's liberalized wholesale electricity markets are considered to be highly complex systems. This is due to, among other things, the specific characteristics of the commodity electricity, e.g., instantaneous balancing of supply and demand, limited storability, and the fact that electricity can only be transported via transmission lines with limited capacities. Other factors that increase the complexity are the various interrelated markets where electricity or related products can be traded, e.g., day-ahead market or derivatives market, and the influence of other volatile markets such as the market for carbon emission allowances.

One important aspect of electricity systems is the reliability, which should be ensured at all times. In liberalized European markets electricity generation companies are not obliged to invest in new power plants. Consequently, electricity markets need to be designed in such a way that there are sufficient incentives for adequate investments. The currently often discussed concept to ensure reliability in Europe is called *energy only* because power plant operators generate their profits mainly from the produced energy but are not compensated for only providing generation capacity that ensures reliability.

In Germany and several other European countries the spot market for electricity, in particular, the day-ahead market auctions organized by electricity exchanges, plays an essential role as it provides a market place to sell or buy electricity and its price serves as a reference for other markets, e.g., future markets or bilateral contracts. In addition, reserve markets are implemented to ensure the short-term reliability of the electricity system.

Two important developments currently altering the economics of European electricity markets are the increasing electricity generation from renewable energy sources and the European market integration. While for a long time mainly nuclear, coal and oil power plants had been installed in Europe, governments have recognized the decarbonization potential of the electricity sector, and there has been a continuous trend to move towards renewables and gas. In particular, the introduction of the EU-ETS and the creation of various policy programs to support the use of renewable energy sources have contributed to this development.

However, the feed-in of electricity generated from photovoltaic and wind power poses challenges to the electricity markets in their current form because in comparison with thermal power plants the generation from these sources is neither projectable nor precisely predictable and typically enjoys a guaranteed feed-in and compensation, respectively. Consequently, operators of conventional power plants are faced with another source of uncertainty that needs to be considered within the unit commitment problem, where an optimal balance of demand and supply under the various technical constraints of the power plants is to be determined. After determining the day-ahead operation schedule, the intraday market, where electricity can be traded at short notice, offers a possibility to adjust the schedule based on updated information, e.g., a recent forecast of renewable generation. The intraday market is likely to gain importance in the next years, as the generation from renewable energy sources is expected to increase further.

Another significant development in the electricity market is that the current borders of the national markets are subject to change; there are ongoing efforts to achieve a single European market. One aspect thereof is the implementation of market-based mechanisms to allocate limited cross-border capacities between European countries. The Central Western Europe (CWE) Market Coupling between Germany, France, Belgium, the Netherlands, and Luxemburg serves as one of the most prominent examples. Market coupling maximizes social welfare, leads to price convergence and helps to balance different supply and demand situation in the interconnected market areas. The integration of markets is a matter-of-fact, thus influencing market prices and profitability of power plants in Europe.

Given the electricity system's complexity, the relevant actors rely on different types of models for decision support. For instance, models are used by regulatory entities to analyze questions related to market design, which is necessary to guarantee system reliability on different levels. Similarly, generation companies rely on electricity market models, for example, in order to examine investment cases. Naturally, market changes need to be reflected appropriately in modeling techniques.

In this chapter, the main elements of the detailed bottom-up agent-based simulation model are described and current extensions to adjust the model to relevant electricity market developments are presented. The aims of this chapter are to present a comprehensive overview of the applied modeling framework for electricity markets and how it can be used to analyze different research questions.

The chapter is organized as follows: Section 8.1 provides a brief overview of the different types of electricity market models and shows the general suitability of agent-based simulation in the context of electricity markets. In Section 8.2, the model's main elements with a focus on agents and markets are described. Exemplary results are presented in Section 8.3. Finally, Section 8.4 concludes with a summary and an outlook.

8.1 Techno-economic models for interconnected markets

The models used for electricity markets can be classified into several categories. Ventosa et al. (2005) identify three major categories in electricity market modeling: optimization models, equilibrium models, and simulation models. Distinguishing features include the mathematical structure, market representation, computational tractability and main applications.

While in Europe the liberalization of electricity markets started in 1996, electricity market models developed beforehand had been mostly optimizing models incorporating the perspective of a single planner, i.e., the government. Through the liberalization, the integration of a market perspective in models has gained importance, which brought forth the development of alternative models such as agent-based models that are able to adequately represent the current market situation where not one central decision maker is found, but several market players pursue their individual goals. In general, agent-based models, which have been developed in quite different disciplines, can provide a flexible environment, which allows considering inter alia learning effects, imperfect competition including strategic behavior and asymmetric information among market participants (Tesfatsion, 2006).

Nowadays, there exists a large number of agent-based electricity market models. Depending on the research focus, the models in the literature will differ from each other with respect to various criteria.

Each agent-based model features a certain agent definition and architecture, which can include several dimensions. In the first place, it is essential to define conceptually what the *agent* represents in the model. In the field of agent-based computational economics agents generally are defined as having a set of data and pre-defined behavioral rules within a computationally constructed world (Tesfatsion, 2006). The agent architecture includes the design of specific agent decision models including adaptive learning algorithms. Market modeling is another large building block of agent-based models. Given the complex nature of wholesale electricity markets and the electricity supply chain, different types of horizontally and vertically integrated markets exist. In order to analyze the existing interrelations between markets, one has to consider these markets with respect to their specific clearing rules. Depending on the spatial coverage of the model, the coupling of interconnected areas might be considered as well. Similarly, agent-based models differ with regard to the time resolution as well as time scale of the simulation. The latter aspects includes, for instance, whether short-term behavior (e.g., spot market bidding strategies) and long-term aspects (e.g., investment decisions) are jointly considered. Another critical aspect of electricity market models is the representation of the electricity system's technical constraints (e.g., techno-economic aspects of generation units, grid constraints.

Three comprehensive reviews showing the large body of agent-based models for electricity markets and their distinctive features are provided by Guerci et al. (2010); Sensfuß et al. (2007); Weidlich and Veit (2008). These literature reviews contain a comparison of the different existing models including the model presented in this chapter.

Having an integrated agent and market perspective, as well as a high degree of flexibility, agent-based simulation models can be used for detailed analyses of electricity markets and interactions therein. Potential applications include market power analysis or market design studies in consideration of the feed-in from renewable energy sources and integrated markets concerning products, time and region.

8.2 Main elements of the applied agent-based model

The subject of modeling is the electricity wholesale market, which is simulated for each hour of a year. Initially, the model was designed for the German market area. However, Europe's electricity markets are all liberalized and set up according to the same fundamental principles, hence, other European market areas can be used to simulate as well with minor adaptations. Market areas are interpreted as one *object* in the programming environment featuring different market elements, agents and input data. In order to simulate different market areas, the respective object is repeatedly instantiated.

One of the key features of the model is the integration of both short-term market developments and long-term capacity expansion planning. Thereby, interactions and feedback loops between short-term and long-term output decisions are considered. Decisions regarding the expansion of capacity, i.e., whether to install a new power plant are influenced by current and future developments in the daily electricity trading as the main source of income and vice versa.

The key modules are markets, electricity supply, electricity demand and regulatory aspects. The main players participating in the wholesale electricity market are modeled individually; small companies are represented in an aggregated form. Different types of market participants are modeled as different types of agents. Each agent takes over certain roles, makes decisions based on specified functions and either takes part in or sets rules for a respective market.

In the following sections, the focus is set on the supply side, i.e., on generation companies, which have to decide on the short-term operation of their existing power plants and the investment in new ones.

8.2.1 Short-term bidding on electricity markets

The short-term operation of power plants is determined by the *SupplyBidder* agent. The agent evaluates the different markets where energy or capacity of thermal power plants can be offered and determines the operation schedule and dispatch of the plants. In accordance with the current situation in Central Western Europe, every *SupplyBidder* daily submits for each available power plant electricity supply bids to the day-ahead market. Besides for thermal power plants, also supply bids for generation from renewable energy sources, e.g., wind or biomass, are regarded. As pumped-storage units can produce or consume electricity, they submit either buy or sell bids. The same applies to the electricity exchange with market areas which are not explicitly modeled. After receiving the bids, the *DayAheadMarketAuctioneer* determines a uniform price for each hour of the next day considering all submitted supply and demand bids.

SupplyBidders are faced with an economic optimization problem, where the offered volume and price of their power plants needs to be determined and which is solved in several steps. Firstly, the available capacity $P_{i,d}$ of a power plant i on a day d needs to be determined. Power plants may not be available at all for a given day due to unexpected issues (e.g., start-up failure), or expected reasons, (e.g., maintenance). As power plants act on other markets as well, the reserved capacity $P_{r,i,d}$ for these markets is not available anymore for the day-ahead market bidding and needs to be subtracted from the net electrical capacity P_i^{net}:

$$P_{i,d} = \begin{cases} P_i^{\text{net}} - P_{r,i,d} & \text{if plant } i \text{ is available on day } d \\ 0 & \text{otherwise} \end{cases} \tag{8.1}$$

Secondly, the bid price is calculated. It consists of three elements: variable costs, start-up costs and a potential markup. Variable costs $c_{i,d}^{var}$ represent the direct costs of producing one unit of electricity and are determined by the fuel price $p_{i,d}^{\text{fuel}}$, the power plant's net electrical efficiency η_i, the price of the emission allowances p_d^{cer}, the CO_2 emission factor of the fuel EF_{fuel} and the costs for operation and maintenance $c_{d,i}^{\text{other}}$:

$$c_{d,i}^{\text{var}} = \frac{p_{d,i}^{\text{fuel}}}{\eta_i} + \frac{EF_i}{\eta_i} \cdot p_{d,i}^{\text{cer}} + c_{d,i}^{\text{other}} \tag{8.2}$$

Changing the mode of operation of power plants, i.e., starting up or shutting down, causes additional costs. Firstly, the material is stressed mainly by temperature changes reducing life expectancy; secondly, for start-ups, fuel is needed in order to reach the operating temperature of a power plant. When determining the bid price the costs from start-up and shutdown processes as an intertemporal restriction can be considered by power plant operators. In the model, this means that for base load running power plants also lower market prices are accepted in order to avoid shutting down the power plant. In turn, start-up costs are added to the bid price for peak load power plants in order to earn start-up costs in hours where the plant is expected to be running. To estimate start-up costs, a price forecast for the next day is made by an agent. The bid price $p_{i,h}$ including start-up costs in hour h is defined as follows:

$$p_{i,h} = \begin{cases} \max\left(c_{d,i}^{\text{var}} - \frac{c_{s,i}}{t_u}\right) & \text{if } \hat{p}_h < c_{d,i}^{\text{var}} \wedge i \in BL \\ c_{d,i}^{\text{var}} + \frac{c_{s,i}}{t_s} & \text{if } \hat{p}_h > c_{d,i}^{\text{var}} \wedge i \in PL \\ c_{d,i}^{\text{var}} & \text{otherwise} \end{cases} \tag{8.3}$$

with

Parameters

$c_{s,i}$	:	Start-up costs
t_u	:	Number of continuous unscheduled hours
t_s	:	Number of continuous scheduled hours
$\hat{p}_h$	:	Predicted price for hour h

Sets

M	:	Set of all operation-ready power plants
$BL \subset M$	:	Set of base load power plants
$PL \subset M$	:	Set of peak load power plants

In addition, *SupplyBidders* can increase the bid price for their power plants by a markup value. According to the standard economic model of perfectly competitive markets, market prices for a respective good are determined by marginal prices at all times. However, in order to cover capital expenditures and fixed costs market prices need to rise above marginal costs of supply at least in some periods. This reasoning is based on the peak-load pricing concept (Boiteux, 1960). One potential remedy is to include an additional markup factor in the bid price of supply capacity. Here, the value of the markup factor depends on the relative scarcity in the market; a higher scarcity induces a higher markup, which is added to the bid price:

$$p_{i,d}^{\text{markup}} = p_{i,d} + markup_h \tag{8.4}$$

After determining the offered volume and price for each hour of the following day, the bids are submitted to the day-ahead market auctions. A comprehensive and formal description of the original short-term bidding algorithm can be found in (Genoese, 2010).

8.2.2 Coupling of interconnected markets

European electricity markets are interconnected via high-voltage transmission lines. As electricity flows according to physical laws and interconnector capacities are limited, these capacities have to be allocated to market participants otherwise, transmission lines might be congested. Management methods are required to avoid congestion and to efficiently use cross-border transmission capacities.

Since 2010, a market coupling approach has been implemented in Central Western Europe, which complies with the European Union's general principles of congestion management (e.g., non-discriminatory, market-based). Market coupling describes the implicit auctioning of interconnection capacity through power exchanges for predefined zones (market or bidding areas). The market coupling operator clears the energy markets of the participating market areas simultaneously and determines implicitly the commercial flows between markets areas as well as the prices. The market coupling approach maximizes the social welfare by optimizing the selection of bids considering limited transmission capacity. The transmission capacity is determined up-front based on defined rules (EPEX SPOT, 2010).

In accordance with the CWE Market Coupling architecture, market coupling is implemented for the day-ahead market, and market participants submit their bid curves to the local power exchanges based on the described method in Section 8.2.1.

The *MarketCouplingOperator* takes over all processes related to the market coupling. For that purpose, the operator receives all day-ahead bids from the local power exchanges. Market coupling itself can be formulated as an optimization problem with the objective to maximize social welfare. As currently only hourly bids with a fixed price are considered, the original algorithm used for the CWE Market Coupling (EPEX SPOT, 2011a) can be simplified, and the mathematical problem is formulated as follows (Meeus et al., 2009):

$$\underset{q_d,\, q_s}{\text{maximize}} \quad \sum_{m \in M} \left(\sum_{d \in D_m} \left(P_d^{\text{bid}} \cdot Q_d^{\text{bid}} \cdot q_d \right) + \sum_{s \in S_m} \left(P_s^{\text{bid}} \cdot Q_s^{\text{bid}} \cdot q_s \right) \right) \tag{8.5a}$$

$$\text{subject to} \quad \sum_{d \in D_m} \left(Q_d^{\text{bid}} \cdot q_d \right) + \sum_{s \in S_m} \left(Q_s^{\text{bid}} \cdot q_s \right) + \sum_{m' \in M'} \left(F_{m \to m'} \right) - \sum_{m' \in M'} \left(F_{m' \to m} \right) = 0 \qquad \forall m \in M \tag{8.5b}$$

$$F_{m \to m'} \leq F_{m \to m'}^{\max} \qquad \forall m, m' \in M \tag{8.5c}$$

$$0 \leq q_d \leq 1 \qquad \forall d \in D_m, \forall m \in M \tag{8.5d}$$

$$0 \leq q_s \leq 1 \qquad \forall s \in S_m, \forall m \in M \tag{8.5e}$$

with

Decision variables

q	:	Bid acceptance rate	[–]
$m \rightarrow m'$	:	Flow from market area m to market area m'	[MWh]

Parameters

P^{bid}	:	Bid price	[EUR/MWh]
Q^{bid}	:	Bid volume	[MWh]
$F^{\text{max}}_{m \rightarrow m'}$	:	Maximum flow from market area m to m'	[MWh]

Indices

d	:	Demand bid
s	:	Supply bid
m	:	Market area

Sets

M	:	Simulated market areas
M'_m	:	Market areas connected to market area m
D_m	:	Demand bids in market area m
S_m	:	Supply bids in market area m

The constraints ensure that supply and buy bids do not exceed their maximum volume (Equation (8.5d) and (8.5e)), that supply and demand including exports as well as imports in market areas are balanced (Equation (8.5b)) and that the limitation on the transmission capacity (Equation (8.5c)) is not violated. In this form, the problem is linear and the optimal solution can be computed with common mathematical programming solvers.

Optimization results are the acceptance rates for each submitted bid and the commercial utilization of transmission capacity. Furthermore, the algorithm determines the market prices of electricity one day- ahead of delivery in the coupled bidding areas and the implicit prices for transmission capacities, which are only different from zero if lines are congested. Prices are sent to the local market areas and processed by the supply agents.

8.2.3 Long-term investment planning

In the model generation companies can also make decisions regarding their long-term capacity extension through investments in new power plants. The responsible agent is called *InvestmentPlanner*.

The basic methodology is based on a discounted-cash-flow valuation of predefined technology options. For that purpose, the *InvestmentPlanner* makes a forecast of the expected hourly electricity prices during the investment period and calculates the expected yearly gross profit. After accounting for fixed costs and capital expenditures, the net present value is calculated.

The quantity of the installed capacity is based on the expected development of market shares within the following five years taking future demand and electricity generation from renewable energy sources into account. As long as the net present value of the investment options is positive and there is need for new capacity, new power plants are built by the *InvestmentPlanner*. After the construction phase, whose length depends on the technology option, the new power plants can generate electricity that can then be sold in the markets.

8.2.4 Input data and technical implementation

For the considered market areas each thermal power plant with a capacity of at least 10 MW is stored together with its main relevant techno-economic characteristics (e.g., net electrical efficiency, variable and fixed costs, yearly availability) in the database of the model.

The model database includes investment options for different power plant technologies with its relevant characteristics and the electricity feed-in from renewable energy sources. The electricity demand is represented by the aggregated consumption of all consumers connected to the public power supply.

For market coupling, transmission capacities between interconnected market areas are required. As not all neighboring countries are always part of a simulation, the electricity exchange with these countries is based on historical values. Prices for fuel and CO_2 emission allowances are required for the calculation of the variable generation costs. Most time series data is stored with hourly values, but sometimes only less detailed values, e.g., for lignite prices, are available.

The model's results include the hourly spot market prices in the simulated wholesale markets, the investments in new capacity and the commercial flows between interconnected market areas. As the model considers the wholesale day-ahead market as the only trading place for electricity, bilateral day-ahead contracts are not part of model's results.

The model is implemented in the object-oriented programming language Java and can simulate each hour of recent historical years as well as future years up to 2050. The simulation runs are comparatively quick in terms of computing time. Yearly runs for one market area last only a few minutes, which is a small fraction of the several hours that optimization models with a similar amount of details may take.

8.3 Applications

The applied model has already been used for various research analyses in the past. For instance, Sensfuß et al. (2008) find a considerable impact of the subsidized renewable electricity generation in the short run on spot market prices in Germany. Futhermore, the impact of emissions trading on electricity prices is explored by Genoese et al. (2007). The authors find for the years under consideration that a large part but not the totality of the emission allowance price is added by the generation companies to the variable costs during the bidding process. A thorough analysis of the model's capacity to adequately reproduce the main characteristics of the German electricity market can be found, for example, in Genoese (2010). In the following sections, additional recent analyses are presented.

8.3.1 Market coupling between Germany and France

Based on the algorithm described in Section 8.2.2, effects from a market coupling between the German and French day-ahead electricity markets are analyzed. Both markets represent the two largest in Europe in terms of electricity consumption and are part of the CWE Market Coupling. To the authors' best knowledge this is the first agent-based approach that includes the coupling of different market areas based on the current market situation.

The simulation of the model coupling is performed for the year 2012. In the *Single Markets* scenario, there is no coupling of the two markets, i.e., no exchange between Germany and France is considered. The *Model Coupling* scenario uses the optimization routine for the coupling of the German and French market areas. The electricity exchange with other countries, e.g., between France and Spain, Germany and Poland, is in both scenarios given exogenously based on historical data.

The *Model Coupling* scenario shows lower average prices than the *Single Market* scenario, whereas the price decrease is stronger in France than in Germany. The more pronounced effect for France can be explained, to some extent, by the supply curves' shapes of the two market areas. The French supply curve has only a gentle slope for a large part of the country's capacity because of the low variable operating costs of nuclear power stations. However, the small part of the remaining capacity consists of notably more expensive fossil fuel-fired units. These units are often called upon in the *Single Markets* scenario. When coupling the markets, the expensive units in France are less frequently used because cheaper electricity can be imported from Germany.

The change in market prices does not imply that all market participants, buyers and sellers, benefit. The results of this simulation indicate that mainly the consumers benefit from the market coupling which is consistent with expectations given a lower average price. The social welfare, i.e., the sum of consumer surplus, producer surplus, and congestion revenue, increases with market coupling, which could be expected, as the clearing algorithm tries to maximize this value.

In the *Model Coupling* scenario the available transfer capacity is fully used in 65 % of the cases. The high usage of the full capacities and the price effect of the coupling can be seen for a period of 100 hours in Figure 8.1. Expanding, e.g., doubling, the capacity amplifies the price reduction in both countries; whereas the additional effect is smaller in France than in Germany, the total price reduction is still stronger in France. In case of sufficient capacity, there are identical prices in all hours, which is equal to the situation of having one completely integrated market.

Regarding only market coupling between two countries, in this case, Germany and France, whereas the exchange with other country is based on historical values, is, of course, a simplification. Germany, for instance, has interconnections with nine countries whereas France is connected to seven countries. Among those countries are some that take part in the market coupling as well, e.g., Austria, Belgium or the Netherlands. Hence, the effects from the market coupling between Germany and France in this chapter might be overstated, as either country would exchange electricity with other countries, if this as well is no longer static and less costly than the exchange with Germany or France, respectively.

The presented results also depend on information which is not publicly available and therefore needs to be estimated, such as the operation and maintenance costs of power plants. Deviations between estimated and real-world values could, of course, alter the results of the simulation.

8.3.2 Role-playing games

Besides the computational model, there exists a laboratory version, where real-life participants can assume the tasks of software agents. Thus, the core agent-based simulation model is supplemented by elements from experimental economics and role-playing games (Genoese and Fichtner, 2012).

In literature, two approaches are distinguished in combining agent-based models and role-playing games. Barreteau et al. (2001) propose a parallel existence of agent-

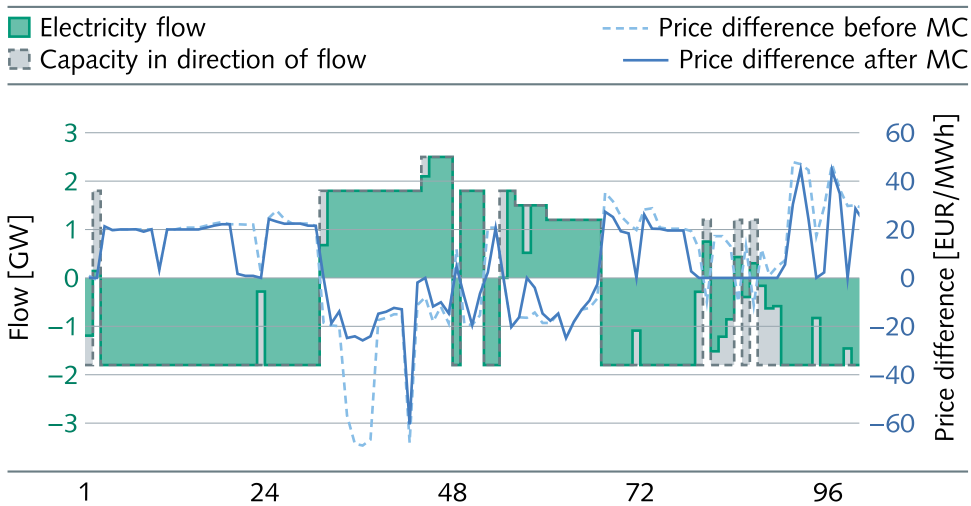

Figure 8.1 I Market coupling. The simulated electricity flow and price difference between Germany and France for a period of 100 hours in 2012 is depicted. In most cases, the available interconnecting capacity of up to 2.5 GW is used to its full extent, yet in some cases, the price difference still exceeds 60 EUR/MWh. If the capacity is not fully utilized, both market areas share an identical price after market coupling.

based models and role-playing games. Hence, the model is rebuilt in a simplified version as a game. The main goal of this approach is to increase the acceptance of the model. Guyot and Honiden (2006) develop an agent-based participatory approach, where real participants are integrated into the model by (partly) controlling the agents' actions. For this, user interfaces have to be developed. In the lab version, the agent-based participatory approach is used.

Currently, in the lab version two modules exist where human participants can interact. The participants either simulate the power trading or the investments in new generation capacity. In the trading module, the participants receive the same information as the computer agents. Each participant has a list of daily available power plants with all the relevant technical and economic data, e.g., installed capacity, fuel costs, and efficiency. In addition, a forecast of the day-ahead prices is presented. Based on this information, the participants submit their bids. When all players have successfully completed their task, the market clearing price is computed analogously to the computational model. The players have the possibility to adapt their strategies in each round in order to maximize profits. In the investment module, the players can carry out investments according to the power and fuel price forecast and by taking into account the decreasing capacities due to the limited technical lifetime of existing power plants.

The players' decisions and chosen strategies can be used to improve the behavior of the computer agents. Computer agents and real participants can coexist as well in the simulations.

8.4 Conclusions and Outlook

Agent-based simulation in general and the applied electricity market model, in particular, are helpful means to analyze different aspects of electricity markets. The market and agent perspective, as well as the flexibility of agent-based simulation models, allow to thoroughly analyze electricity markets and interactions therein. The model is a detailed bottom-up simulation model, which integrates short-term market operations and long-term capacity planning whereas the most important market participants are represented by different agents. The model has already been used for various analyses in the context of electricity markets.

Given the continuously changing economic and regulatory environment in the power sector, several enhancements to the model are currently in progress. In order to reflect the European market integration, the model scope is extended to several market areas, which can be simultaneously run and coupled. Model coupling clears the energy and capacity markets simultaneously and determines an optimal solution to the plant dispatch in the interconnected market areas considering limited commercial transfer capacities. The model coupling routine presented in this chapter offers a socially beneficial opportunity to interconnect electricity markets compared to a situation where no market coupling occurs. The results for Germany and France show that the average market price is lower in both countries, whereas the price decrease is stronger in France than in Germany.

The applied methodological approach has some limitations nonetheless. Regarding the supply of electricity, additional technical constraints concerning the operation of power plants, e.g., minimum downtimes or partial efficiency levels, could further improve the model. Furthermore, the perspective is limited to the supply of electricity, which differs from the real world situation where also the heat demand influences the usage of combined heat and power plants.

Given the flexible modeling framework, future model extensions could include the development of a generally scalable model version to simulate micro-systems as well as larger system, e.g., Europe, with additional market elements, e.g., intraday market. Concerning the decision-making process of agents, the refinement of the investment module and the integration of different aspects of uncertainty is another possibility to extend the model. Regarding the design of electricity markets, the remuneration of power plants by capacity mechanisms in order to ensure system reliability is another topic of research that is currently explored within the model.

Chapter 9
Cross-border effects of capacity remuneration mechanisms: The Case of the Swiss Electricity Market

European electricity markets are becoming more and more integrated as a consequence of the internal market guidelines and the so-called Energy Union strategic framework of the European Commission (1997, 2003a, 2009). The integration of the electricity markets is mainly driven by two intertwined processes: On the one hand, European markets are more tightly linked by implicit auctions and combined by the so-called Price Coupling of Regions run by eight European power exchanges (EPEX SPOT, 2018c). On the other hand, the physical transmission grid is expanded, and in particular, the interconnectors will be further enhanced according to the Ten Year Network Development Plan (ENTSO-E, 2018a).

As a result, different cross-border effects can be observed: e.g., market clearing is determined in a way that energy flows from market areas with higher prices to those with lower prices resulting in a convergence of electricity prices in connected market areas given that sufficient interconnection capacity is available. The price convergence stops if the available interconnector does not allow a further flow of electricity and, in this case, a certain price difference remains. However, an additional interconnection line between two market zones can increase the price assimilation resulting in positive welfare effects (Ringler et al., 2017).

In the case of a small country neighbored by large markets (asymmetrical market areas), the cross-border price effect can be strong. Therefore, as a case study, Switzerland serves as a useful example for analyzing the impact of large neighboring markets on a smaller one. Because the analysis by Dehler et al. (2016) shows a strong interdependence of wholesale electricity prices of Switzerland and its neighbors (Austria, France, Italy, and Germany) due to tightly interconnected electricity grids. For instance, the electricity price decline between 2011 and 2016 in the Central Western European countries driven by a renewable expansion and low prices for EU-ETS emission allowance resulted in lower prices also in the Swiss electricity market. This price decline can be welcomed from the consumer perspective but has a lowering effect on producer rent and the profitability of power plants (Bublitz et al., 2017; Hirth, 2018; Kallabis et al., 2016). This might yield not only for thermal capacities but also for the dominant hydropower plants in Switzerland.

These developments are expected to intensify in the near future, as some neighboring countries changed the design of their wholesale electricity markets in the past few years, which can put additional pressure on Swiss wholesale electricity prices. For instance, Germany is planning to introduce a strategic reserve (SR) to ensure generation adequacy in scarcity times (BMWi, 2017a). Also, France implemented a CRM, a decentralized capacity market, to ensure generation adequacy and incentivize DSM measures in peak load times (Bublitz et al., 2019). As the yearly traded volume in the French and German electricity markets is considerably larger than in other European markets, their decisions strongly influence the neighboring markets, especially the comparatively small ones. In this context, the question arises as to whether the Swiss market also requires new instruments to ensure long-term generation adequacy by incentivizing national investments and retrofitting.

Therefore, the goal of this study is to investigate the cross-border effects of CRMs on electricity prices, investments, and thus on the long-term generation adequacy in such connected market areas by applying a power market model based on agent-based simulation using Switzerland as a case study. This approach allows the consideration of individual decisions of market players and the analysis of market equilibria based on these decisions.

The remainder of the chapter is structured as follows: Section 9.1 summarizes the current literature on cross-border effects with regard to CRMs and deduces the research gap in this context. Section 9.2 describes the applied simulation approach focusing on modeling CRMs in an electricity market model. The results, including investments, price impact, and the generation adequacy, are discussed in Section 9.3. Finally, in Section 9.4, the methodology is critically evaluated, and the main conclusions as well as policy implications are derived in Section 9.5.

9.1 Literature review

One of the difficulties encountered in the analysis of cross-border effects is the large number of possible influences, such as the number and the market size of the countries considered. In addition, the levels of competition and the respective market designs can influence the results (Meyer and Gore, 2015). Thus, it is difficult to derive general conclusions. This fact might serve as an explanation of why the literature predominantly focuses on a single market scenario, and the research on spillover effects of capacity remuneration mechanisms is lagging behind (Lorenczik, 2017). However, without a sound theoretical framework on cross-border effects, ensuring generation adequacy at a regional level in an efficient manner remains a major challenge (Glachant et al., 2017). This is further complicated by the fact that cross-border effects can emerge in a non-linear manner (Boffa et al., 2010).

A question frequently examined in the literature is whether free-riding occurs if a neighboring country introduces a CRM. For example, Bhagwat et al. (2014, 2017c) study cross-border effects in two symmetrical market areas differing only in their design. Whereas an EOM does not limit the effectiveness of the neighboring capacity market or SR, vice versa, two effects can be observed: On the one hand, the consumers in the EOM are free-riding on the consumers in the neighboring market where a CRM is implemented. On the other hand, the dependence of the EOM on the neighboring markets is increasing. Similarly, Meyer and Gore (2015) find that the unilateral implementation of a CRM, either in the form of reliability options or a SR, weakens investment incentives in the neighboring market. Cepeda and Finon (2011) analyze the cross-border effects of three different market designs (EOM, price-capped EOM, forward capacity market). They find that in the long-term, the market area with an EOM does not benefit from the adjacent market area where a price-capped forward capacity market is implemented, and even negative externalities can arise in the form of a higher average price and lower reliability.

Lorenczik (2017) observes that the negative effect of price caps intensifies if a market is connected to neighboring markets and, thus, generation capacity and welfare further decrease. Yet, vice versa, national price caps do not seem to have a significant adverse effect on neighboring countries. Contrary to other studies, it is claimed that capacity payments do not exert a significant positive effect on the security of supply in neighboring countries.

Not only between a market with and without a CRM, spillover effects can occur, but also between markets with different CRMs. In a scenario where a SR is introduced in one market and a capacity market in the other, Bhagwat et al. (2014, 2017c) observe negative spillover effects of the capacity market on the SR resulting in, e.g., a lower reserve margin in the market with the SR. Elberg (2014) investigates two symmetrical market areas in which either a SR or capacity payments have been implemented. On an isolated basis, both mechanisms lead to an efficient outcome. However, in a combined evaluation, the SR shows worse results due to redistribution effects, as the consumer welfare decreases in the area of the SR, whereas it increases in the adjacent area.

In some cases, CRMs are also investigated in real-world case studies. For example, Ochoa and Gore (2015) investigate the welfare and security of supply in the Finnish electricity market under consideration of potential benefits and risks arising from the connection to the Russian market. In case the electricity imports from Russia were reliably available, the expansion of transmission capacities would be recommended. However, as their reliability is doubtful, it is recommended to build up national generation capacities and maintain a SR. In another analysis, Ochoa and van Ackere (2015b) examine cross-border effects in Colombia–Ecuador and France–Great Britain. They conclude that the potential benefits are strongly linked to market complementarity and that policy measures to exploit these benefits without distorting market signals must be carefully evaluated, especially if large seasonal storage capacities exist, which might be used extensively during shortage situations in the neighboring country and subsequently are unavailable for national usage. In a follow-up study, Ochoa and van Ackere (2015a) once again analyze the markets of Colombia–Ecuador and find that the relative market sizes and the size of transmission capacities have a significant influence on potential cross-border benefits.

One of the remaining key challenges in evaluating generation adequacy is to assess the contribution of neighboring countries in order to avoid over- or undercapacity. Mastropietro et al. (2015) investigate possibilities to remove barriers preventing foreign participants in Europe from participating in external capacity mechanisms without reducing the short-term efficiency of the electricity market. They propose that capacities should be procured via zonal auctions, which take into account the maximum transmission capacity of the interconnection, and that capacities should not be allowed to participate in different national CRMs. Finon (2014) investigates the differences between explicit and implicit cross-border participation. In the long term, he states that excluding cross-border participants does result in neither a significantly lower efficiency nor a distortive effect on the competition. From a European perspective, however, the explicit consideration of capacities can be advantageous. Furthermore, it can be noted that the introduction of a CRM in a neighboring country considerably increases the pressure to introduce a national mechanism, in order to protect the market against possible harmful consequences (Bhagwat et al., 2017c; Gore et al., 2016). Another possibility is to focus on supranational coordination (Hawker et al., 2017; Neuhoff et al., 2016; Osorio and van Ackere, 2016).

At this point, it needs to be emphasized that the uncoordinated introduction of CRMs in a tightly interconnected continental electricity system, such as the European system, can distort price signals and even impair the security of supply in a neighboring market. However, despite existing research, cross-border effects of CRMs have not yet been fully explored and, in particular, the impact on tightly connected real-world markets remains to a large extent unknown. Therefore, to deepen the understanding and identify adverse cross-border effects of CRM, a case study is carried out, in which the Swiss electricity market is analyzed. The Swiss market has two unusual characteristics that make it particularly suitable for the analysis: On the one hand, as a small market, it is strongly influenced by large neighboring markets (Dehler et al., 2016) and, on the other hand, it possesses mainly complementary and opportunity cost-based generation technologies, i.e., a significant share of hydro storage capacities (Swiss Federal Office of Energy, 2018a). As the opportunity costs are often based on results from neighboring markets, the cross-border influence is particularly strong.

9.2 The agent-based modeling approach

In this section, the methodology for analyzing the cross-border effects of different market designs is presented. To this end, an agent-based simulation model with the focus on Switzerland and adjacent countries has been developed further and applied (Section 9.2.1–9.2.3). Section 9.2.4 outlines the modeling of CRMs that are newly introduced or have already been implemented in the considered market areas. In order to take into account the specific characteristics of the Swiss electricity market, extensions had to be made in particular for hydropower plants, which are presented in Section 9.6.1.

9.2.1 Overview

In order to model the regarded electricity markets, an agent-based simulation approach is used and extended (e.g., Ringler et al., 2017). To analyze electricity markets in a dynamic environment, agent-based simulation has already been applied widely (Guerci et al., 2010; Ventosa et al., 2005; Weidlich and Veit, 2008) as it offers the possibility of integrating the individual market participants with a high level of detail (Tesfatsion, 2003). The behavior of the agents can be best described with the concept of bounded rationality (Simon, 1986), which states that all decisions are made on the basis of the agents' limited knowledge about the present and imperfect information about the future. Therefore, the result of the model is not a long-term, optimal equilibrium determined by a central decision-maker, but depends on the decisions of all agents, who pursue individual strategies to reach their goals. Thereby, the market development under consideration of the complex interactions can be investigated even in non-equilibrium situations, and new insights can be gained (Epstein, 1999). For instance, this also means that the demand may not be met by the supply capacity as agents can invest less than the required capacity in the case of an expected negative NPV of new investments. Besides, it is also possible for power plant operators to submit strategic bids above the variable costs.

In the applied agent-based bottom-up simulation model, individual agents are major national and international actors representing the main generation companies. The model integrates the short-term dispatching of generation units with an hourly time resolution (Section 9.2.2) and the long-term capacity planning with regard to conventional power plants (Section 9.2.3).

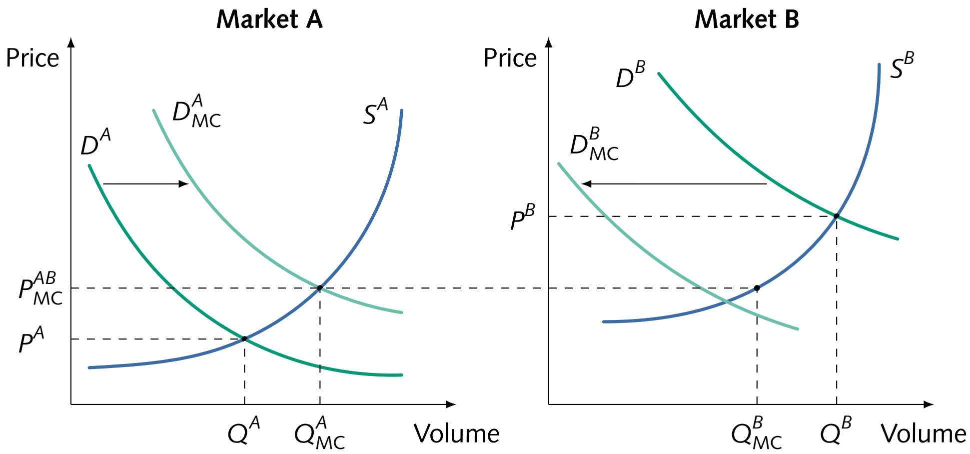

Figure 9.1 | Market coupling with sufficient transmission capacity. As sufficient transmission capacity between the two interconnected markets is available, prices converge to P^{AB}_{MC} and the economic welfare increases. However, this does not imply that each market participant is better off. For example, consumers in market *A* have to pay a higher price than they would pay without market coupling.

9.2.2 Day-ahead market

In order to analyze in particular the interactions of the different market areas, each market is implemented as an optional module and interconnected to its neighboring markets via the available transmission capacities. In recent years in Europe, market coupling has made steady progress and, in 2015, a flow-based approach was introduced (EPEX SPOT, 2016), replacing the ATC-based approach used before (EPEX SPOT, 2011a). As cross-border effects are strongly influenced by the way market coupling is implemented, an algorithm was chosen that resembles the actual market design and can be divided into the following steps:

First, in each area, agents are called upon by a national market operator to submit bids for the day-ahead market for each hour of the following day. The bids are based on the variable costs of the generation capacity units but can also include a markup in scarcity hours (Keles et al., 2016a). Next, all national bids are submitted to a central operator that applies a welfare-maximizing market clearing algorithm subject to the

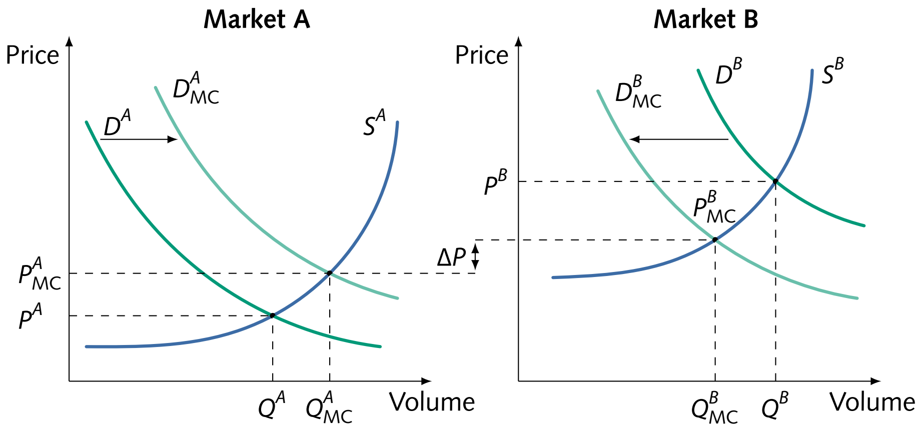

Figure 9.2 | Market coupling with insufficient transmission capacity. As there is lower-cost generation capacity available in Market *A*, Market *B* imports electricity. Thereby, a smaller part of its local demand D^B_{MC} has to be covered by its own supply S^B and the price in market *B* decreases. In market *A*, the situation is exactly the opposite. Generation capacities from market *A* serve an overall higher demand D^A_{MC}, thus more expensive capacities are required, and the price in market *A* rises. However, as only insufficient transmission capacity is available, no uniform price is reached, but a price difference of ΔP remains.

available interconnection capacity as well as the balance of supply and demand in each market area.[1] As shown in Figure 9.1 and Figure 9.2, the algorithm leads to a convergence of market prices and, in the case of sufficiently large transmission capacities, identical prices.

9.2.3 Capacity expansion

The model contains an investment planning module, which is executed once a year within the chosen time horizon. Thereby, different investment options of flexible power plants are compared according to a certain economic criterion, e.g., the net present value. Potential revenues for power plants can be generated from selling electricity in energy spot markets as well as from participating in different CRMs,

[1] For further details, for example, the mathematical formulation of the market clearing problem, refer to Ringler et al. (2017).

e.g., a central capacity market or a SR, depending on the respective market area configuration. Investment agents in all market areas evaluate different power plant options. Data and assumptions on which the prediction is based are future electricity demand as well as fuel and emission price developments in the following years. Based on the data, a price forecast is firstly made for future prices in the respective market areas. Each agent a from all market areas calculates the NPV for each available investment option j according to Equation (9.1).

$$\mathrm{NPV}_{j,a} = -I_{0,j} + \sum_{t=1}^{n_j} \frac{-c^{\mathrm{fix}}_{t,j} + \sum_{h=1}^{8760} \max\{p^{\mathrm{prog}}_{h,t,a} - c^{\mathrm{var}}_{h,t,j}, 0\}}{(1+i)^t} \quad \forall j, a \tag{9.1}$$

Calculation of the NPV is based on the investment payment I_0, the economic lifetime n, interest rate i, fixed costs c^{fix} price forecast p^{prog} and variable costs c^{var}.

Investment options are predetermined exogenously based on the scenario (Table 9.2) and represent a specific flexible power plant type, such as a gas turbine. The options include all economic—e.g., investment I_0 or investment horizon n—and technological parameters—e.g., efficiency or net capacity—that vary over the simulation period. In addition, future technological developments such as carbon capture systems are taken into account in various investment options.

For calculation of the expected annual revenues of the spot market, an hourly electricity price forecast p^{prog} is used. The price forecast for the NPV calculations works analogously to the determination of the spot market price by applying a welfare maximizing market coupling. The variable costs c^{var} for each hour h of the year t are deducted from p^{prog}. As a power plant only produces if at least the variable costs are covered, all negative cash flows are excluded neglecting must-run conditions, start-up costs, and minimum downtimes. For calculation of the variable costs, fuel prices and carbon certificate prices are assumed to be the same in all market areas.

A list with the NPV values of all power plant options is created for all agents A from all market areas. From this, the option j^* is selected that reaches the highest positive NPV* of all agents:

$$j^* = \max \mathrm{NPV}_{j,a} \qquad \forall j : \mathrm{NPV}_j > 0 \text{ and } a \in A \tag{9.2}$$

Each investment increases the totally installed capacity and thus influences prices. Consequently, no investor would make an investment with an initial positive NPV, if it affects prices to such an extent that the own new investment becomes unprofitable. Therefore, a new price forecast is calculated after each investment decision for option j^*. Subsequently, j^* is revaluated with the new price forecast. If the NPV* of j^* is still positive, the agent invests in option j^*. If the NPV* of j^* is not positive, a new price forecast is calculated with the option with the second highest NPV and so on until an investment is made. If no investment with a positive NPV is available, the algorithm terminates, and no further investments are made in the simulation year. The investment process is repeated every year of the model horizon.

9.2.4 Modeling capacity remuneration mechanisms

In recent years, some countries have introduced CRMs, thus making it necessary to extend the model with this very feature. The model is able to consider SR and other types of CRMs (Bublitz et al., 2015a; Keles et al., 2016a). For this analysis, only the SR for Belgium and Germany as well as a decentralized capacity market for France and a central capacity market for Italy are applied (see Figure 9.3). The payments of the modeled mechanisms are also taken into account for the NPV calculation described in Section 9.2.3.

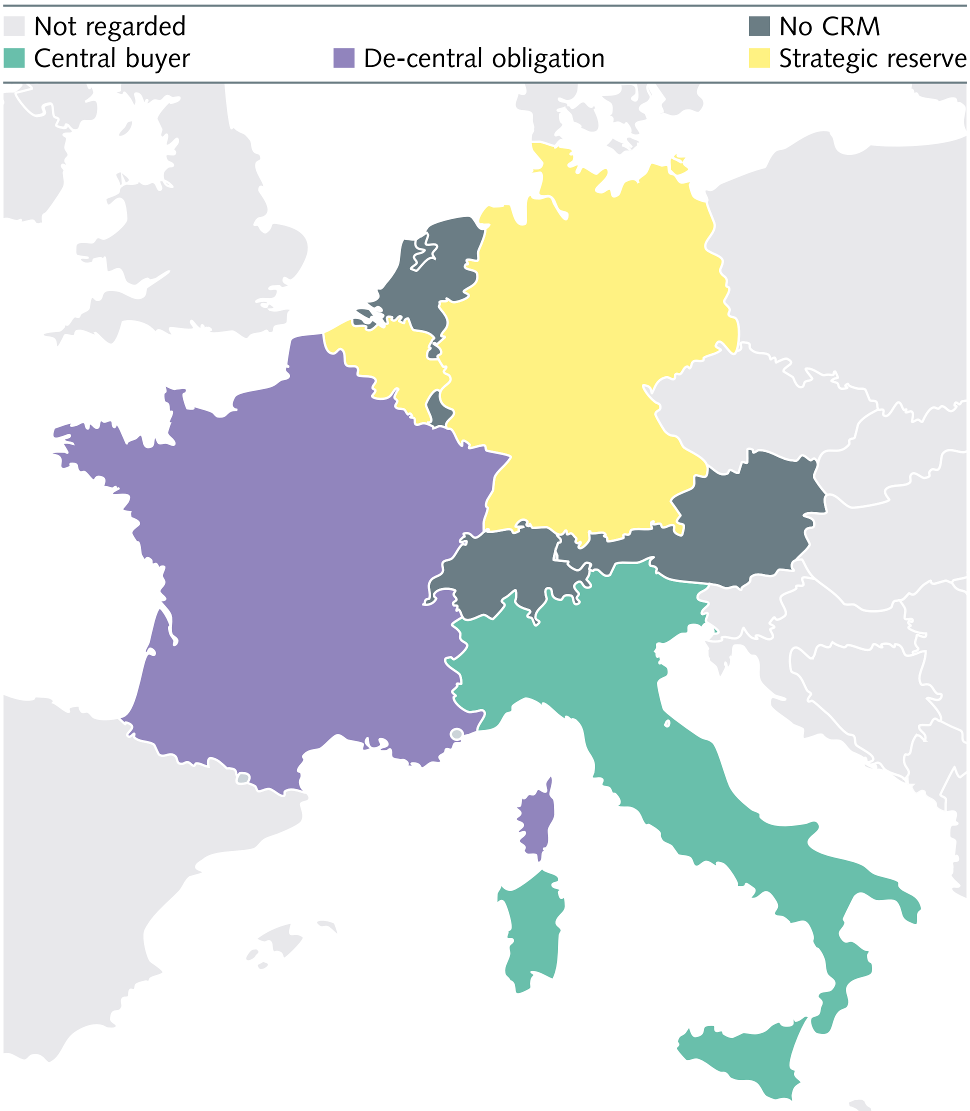

Figure 9.3 | Market areas. In the model, the following countries are included with the already implemented and planned capacity remuneration mechanisms: Austria, Belgium, France, Germany, Italy, Luxembourg, the Netherlands, and Switzerland.

Strategic reserve

Every year, the national transmission system operators in Belgium and Germany organize an auction to procure the necessary capacity for the SR. In order to participate, a generation unit must be available within a certain time, i.e., after a cold start time of less than 10 hours. The selection of generation capacity is determined by the submitted capacity price without considering electricity generation costs. Generators offer their capacities based on their respective annual fixed and opportunity costs. The opportunity costs correspond to the expected lost profits from the other markets, as contracted entities are prohibited from participating in other markets. This restriction remains in effect even after expiry of the contract term and hence obeys the no-way-back rule. Once a power plant is part of the SR, its operational control is carried out by the transmission system operator. The reserve is used only in extreme situations when no balance between supply and demand can be achieved. In this case, the operator offers the reserve in the day-ahead market at the maximum allowed price. The generation units are activated in the order of their variable costs: First, the unit with the lowest variable costs is dispatched, then the more expensive ones. The owner receives a recompensation for the costs additionally incurred during the operation time, e.g., fuel and carbon costs. For further details regarding the implementation of the SR refer to Bublitz et al. (2015a).

Capacity markets

The implementation of the French capacity market (Réseau de transport d'électricité [RTE], 2017), which was particularly developed for this investigation, is described in detail in Zimmermann et al. (2017) or Kraft (2017). Firstly, the reference capacity demand (based on the future annual peak demand) including an exogenously defined security factor is calculated. Depending on the reference capacity, the capacity obligations of the obligated parties, i.e., supply companies and large consumers, are specified depending on their shares in total peak demand, so that each obligated party has to cover the amount corresponding to its own demand.

Secondly, the supply price of the generation capacities is determined due to the expected income on the electricity market for each generation unit based on the yearly difference costs. Difference costs are defined as the gap between the yearly income on the energy market and the required income to break even a generation unit's profitability. Finally, annual payments are derived due to the capacity obligations and the difference costs of the supply units.

The central capacity market with capacity options, applied, e.g., in Italy, is based on the Forward Capacity Market, which is currently implemented in the market area of the US system operator ISO New England (2014), and is adjusted to the Italian market area, which is outlined in Keles et al. (2016a). In the model, with a lead time of four years, the regulator agent determines the conventional capacity requirement which is calculated based on the forecasted peak load in the respective year of execution minus the contribution of RES to the generation adequacy (on the basis of predefined capacity credits). The regulator, as the central agent, buys the whole capacity for the market area in the model including all reserve margins based on a certain demand curve (Cramton and Stoft, 2005). Afterward, the generation units receive this payment.

9.2.5 Output

One of the main outputs of the model are the hourly spot electricity prices for each market area. These electricity prices reflect both the national situation, e.g., market design, demand, and generation mix, as well as developments in interconnected markets, e.g., welfare effects and cross-border flows. Therefore, determining the profitability of existing and new generation units is also a result of this study. Given the possibility of varying model parameters (e.g., with certain CRM activated) and input data (e.g., fuel and carbon prices varied), the agent-based simulation model is suitable to analyze a range of different scenarios. Several investigations have been conducted in the past (e.g., Keles et al., 2016b) using the selected modeling approach. In order to analyze cross-border effects, the model has been improved with regard to the methodology and the spatial resolution. The methodological extensions are inter alia the implementation of the French capacity market as well as the hydropower dispatch module (Section 9.6.1), in particular for Austria and Switzerland. Furthermore, the long-term price forecast, which is used in particular in the investment planning module, as well as the investment planning module itself have been improved regarding the consideration of market coupling effects. Geographical extensions include the market areas of Switzerland, Italy, and Austria, whereas, before the extension, the model was limited to the Central Western European (CWE) market area. (See Keles et al., 2016a; Ringler et al., 2017)

9.3 Case study: Switzerland

In this section, a scenario framework will be defined in accordance with the modeling approach (Section 9.2). Therefore, assumptions are made for the development of electricity demand, fuel and carbon certificate prices, and the costs of generation technologies.

This requires the selection and processing of large amounts of data (Table 9.1) to be used in the scenario runs (Table 9.2). The EU Reference Scenario (European Commission, 2016c) was used to derive fuel and carbon prices. All of the flexible fossil power plants in the modeled areas are based on the S&P Global Platts (2016) power plant database. Regarding the market coupling, the trading capacities between the market areas are derived from 50Hertz Transmission et al. (2018) and ENTSO-E (2018a). Investments in new flexible power plants as well as assumptions of fixed and additional variable costs (in addition to the costs of fuel and carbon certificates) for the power plants are based on Schröder et al. (2012). Due to the high resolution of the model, hourly RES feed-in and electricity demand profiles (year 2015) are used as initial data taken from ENTSO-E (2018b) and Swissgrid (2015). The yearly development

Table 9.1 | Input data. In this table, an overview is provided over the main data used in all scenarios. Due to the large amount of different data required, many different sources are used.

Input data type	Resolution	Switzerland	Other countries
Conventional power plants	Plant/unit level	Based on S&P Global Platts (2016), extended with own assumptions	
Fuel and carbon prices	Yearly	European Commission (2016c)	
Investment options	Yearly	Schröder et al. (2012)	
Transmission capacity	Yearly	ENTSO-E (2018a), 50Hertz Transmission et al. (2018)	
Electricity demand and RES feed-in	Hourly aggregated per market area	Prognos (2012) (Scenario C&E), ENTSO-E (2018b), Swissgrid (2015)	European Commission (2016c), ENTSO-E (2018b)

of the demand and the RES feed-in volume is taken from European Commission (2016c) for the EU countries and from Prognos (2012) (Scenario C&E) for Switzerland. All profiles are scaled according to the underlying development in the modeled years. Hydropower plants play a crucial role in the Swiss electricity market. The aggregated capacities of run-of-river, seasonal hydro storage, and pumped storage power plants kept constant at 16.6 GW in total and are taken from Swiss Federal Office of Energy (2018d).

In order to examine the effects of the CRMs in detail, various scenarios and sensitivities are calculated using the agent-based model for a time horizon from 2015 to 2050 to evaluate the individual market designs for the simulated market areas. These are shown in Table 9.2.

Table 9.2 | Scenarios. The applied market designs for the different scenarios for each country are described. Whereas CRM Policies represents a scenario with currently implemented policies, the counterfactual EOM scenario and DE Strategic sensitivity are used to analyze the effects of CRMs.

	EOM	CRM Policies	DE Strategic reserve sensitivity
Austria	EOM	EOM	EOM
Belgium	EOM	SR	SR
France	EOM	DCM†	DCM†
Germany	EOM	SR (5 GW)	SR (2 GW)
Italy	CB*	CB*	CB*
Netherlands	EOM	EOM	EOM
Switzerland	EOM	EOM	EOM

* Central buyer.
† Decentralized capacity market.

9.3.1 Wholesale price development

The EOM scenario is characterized by the fact that only EOMs are implemented in all of the modeled markets. This means that all income from flexible power plants is generated by the sale of electrical energy on the wholesale electricity market. The CRM Policies scenario describes the currently implemented and decided market designs in the modeled market areas/countries. It is a close-to-reality representation of the circumstances prevailing at the time this investigation was being processed.

Looking at the simulated wholesale prices in the EOM (Figure 9.4) and in the CRM Policies scenario (Figure 9.5), it is immediately visible that the prices in France are clearly below the prices for all other market areas until approximately 2035. The reason for this is the high proportion of nuclear power plants in France, which are not affected by rising carbon certificate prices and set the prices at a lower level in France due to their low marginal costs. Due to the limited trading capacities between the countries, the other market areas can only partly profit from these low prices. Moreover, the price-increasing effects of exchange trades with Spain and Great Britain (which are

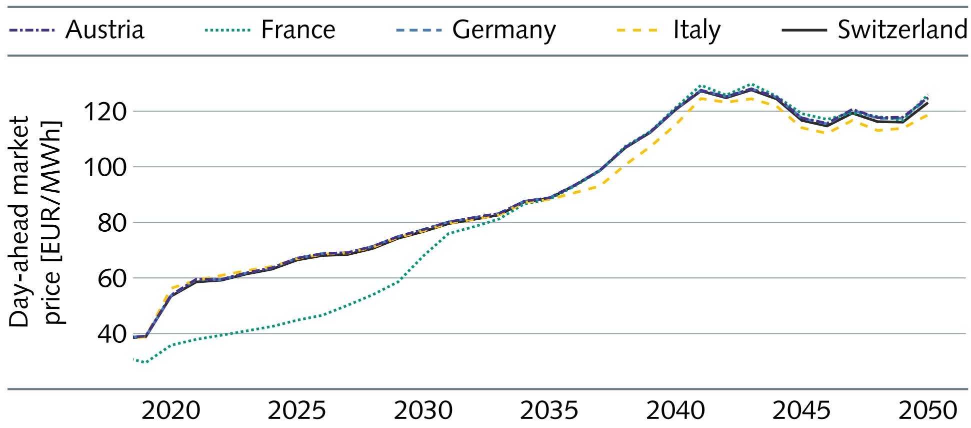

Figure 9.4 | Price development in the EOM scenario. The simulated wholesale prices in the EOM scenario show a strong increase. With the decommissioning of nuclear power plants, French prices rise to a similar level as in other market areas.

connected to the French grid and tend to have a higher price level) are missing in the model due to the chosen system boundaries. This leads to large deviations between the French prices and the other market prices until trading capacities between the modeled countries are substantially increased. In addition, few new nuclear power plants are built in France during the time horizon of the analysis (only towards the end of the simulation period), but rather gas-fired power plants, which in terms of prices align with the other market areas. This can be observed in both scenarios. Therefore, from 2035 onwards, prices in the EOM scenario rise significantly due to scarcity prices within several hours caused by less installed capacity and increasing carbon certificate prices. The average prices in the model in the years 2041 and 2043 are thus over 120 EUR/MWh in the EOM scenario. In the following years, however, the average price is observed to fall again, because these prices again incentivize new investments.

In all modeled market areas, prices are developing in a similar way. Only Italy has average prices slightly below the other areas considered from 2035 onwards. These differences are due to the still limited exchange capacities to neighboring countries

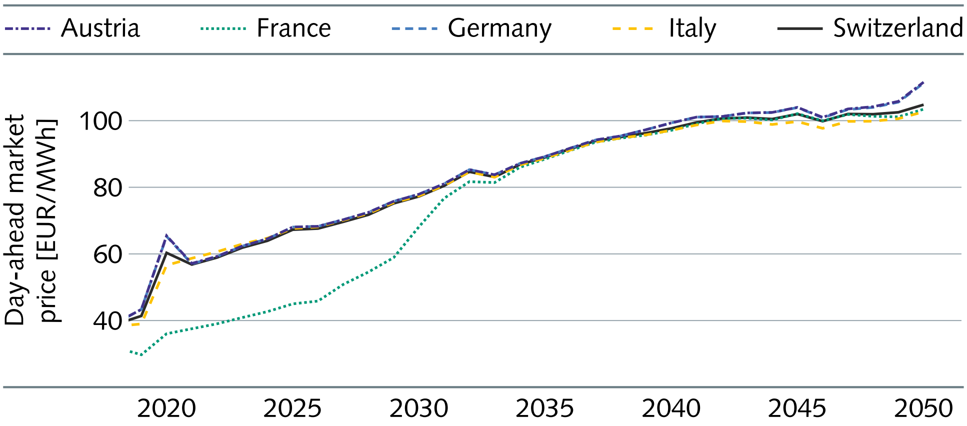

Figure 9.5 | Price development in Switzerland. The simulated prices in the CRM Policies scenario also show a strong increase, although the overall level is lower than in the EOM scenario.

together with high RES production in Italy, so that it is no longer possible to export more electricity in the corresponding hours. E.g., in the year 2043, Italy on the average generates 39 GW from RES in the hours with fully used export capacities. This RES production lowers the average wholesale price. From 2035, the picture is similar for the CRM Policies scenario as in the EOM scenario, with the difference that the average prices are significantly lower. The absolute price deviations of the wholesale market prices of the different scenarios are at the beginning (until 2023) only caused by the introduction of the SR in Germany because the power plants will be taken out of the market. Until 2035, the prices of both scenarios are almost the same; the EOM average prices are even slightly below the average prices of the CRM Policies scenarios. From 2035 onwards, however, prices deviate significantly due to the occurrence of scarcity caused by an insufficient supply in various market areas in the EOM scenario (Figure 9.6). The prices remain lower (see Figure 9.5) due to sufficient capacities in the CRM Policies scenario.

For Switzerland, this deviation of the average prices is shown in Figure 9.6. The maximum difference between the yearly average prices of the EOM scenario and

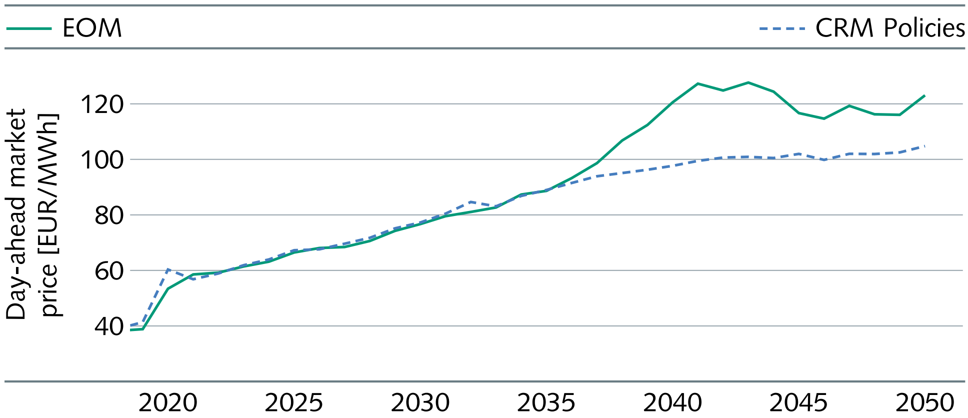

Figure 9.6 | Swiss wholesale prices. In the long term, the simulated prices for the CRM Policies scenario are substantially lower than in the EOM scenario as Swiss consumers benefit from increased abroad generation capacities.

the CRM Policies scenario is more than 27 EUR/MWh in some years after 2035. This high price difference is, of course, due to the higher flexible capacities in France and Italy, which are available at any time. The neighboring countries also profit from the high installed capacity that is signaled by fewer hours in which the market cannot be cleared (Section 9.3.3).

Regarding the prices and the capacity development, the picture is ambivalent for Switzerland. On the one hand, less will be invested in the CRM Policies scenario, prices are lower than in the EOM scenario, and Swiss hydropower offers enough capacity at all hours to ensure that the wholesale market can always be cleared. However, on the other hand, compared to the neighboring countries, the EOM scenario does not have many hours in which the market does not provide sufficient supply, but at significantly higher prices. However, CRMs also causes costs (and could lead to inefficient investments), but this is not relevant to Switzerland because these costs for CRMs are normally allocated within the countries.

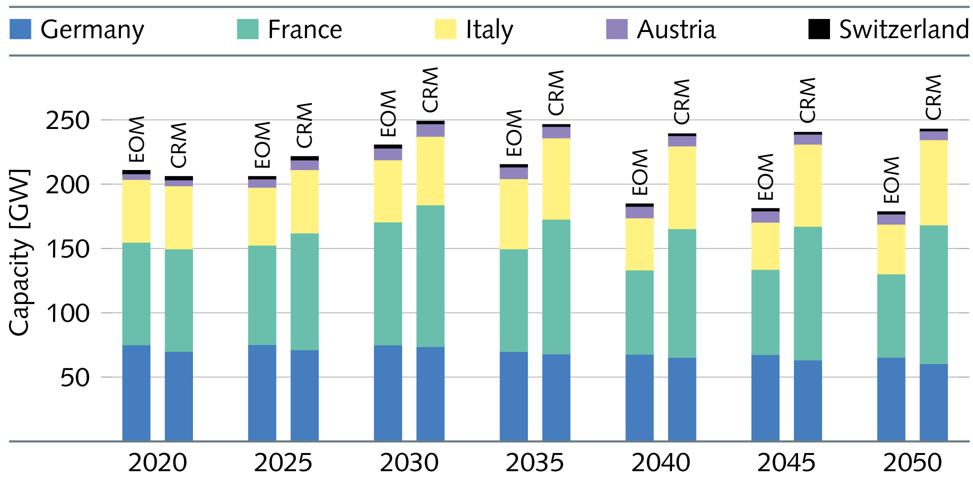

Figure 9.7 | Cumulated conventional capacity. The main differences between the EOM and in the CRM Policies scenario can be seen in France and Italy. There, the introduction of capacity markets leads to higher capacities from 2025 onwards and to a more constant conventional capacity development than in the EOM scenario.

9.3.2 Generation capacities

As CRMs had already been established in some markets at the time of the preparation of this study, the EOM scenario serves as a benchmark. In the EOM scenario, the total installed conventional capacity across all countries decreases, with the exception of Austria. This can be explained by overcapacities, especially in Germany, and by better counterbalancing effects across the various market areas. For instance, market coupling and expansion of trading capacities allow larger volumes of energy exchanges across countries. However, there is a short-term increase in capacity in 2030 and 2035 in the model runs (Figure 9.7). This can essentially be explained by the closure of large nuclear capacities in France, so that with a (purely hypothetical) assumption of the maximum operating life of nuclear power plants being 50 years, starting in 2027, their total capacity shrinks from over 60 GW to less than 10 GW within 15 years excluding new investments (Zimmermann et al., 2017). This leads to raised prices in the forecast module in consecutive years and in some cases to anticipated investments

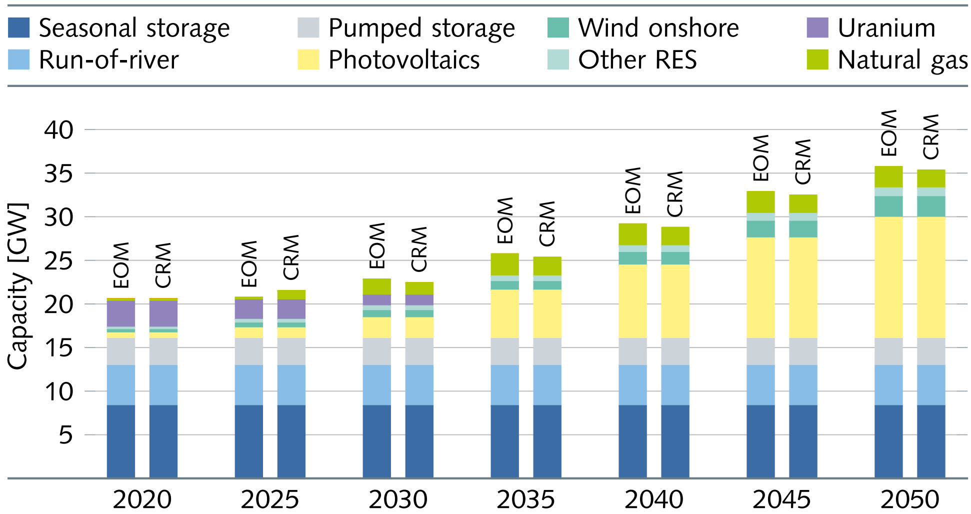

Figure 9.8 | Swiss capacity in the EOM and CRM Policies scenario. The most significant developments are the complete decommissioning of nuclear power plants by 2035, which are being replaced by new investments in gas-fired combined cycle power plants and the expansion of renewable energies, especially photovoltaics.

in new power plants. However, after 2035, the capacity falls back below the level of before 2030 both in France and in all countries considered. After 2035, the reason for the reduction of the installed conventional capacities is the growth of RES in all countries.

However, Austria is an exception, because of the newly introduced market splitting between Austria and Germany (since October 2018) and the merely static exchange with the Czech Republic, Hungary, and Slovenia without price effects. The latter issue could distort prices to such an extent that investments in Austria appear profitable in the model because of high price forecasts due to low installed capacity. For better illustration, Figure 9.7 shows the conventional capacity development without RES.

Figure 9.8 shows capacity development in Switzerland, including all RES capacities, broken down by the respective generation technologies. Whereas the nuclear power plants will be completely phased out by 2035 due to the assumed maximum lifetime of 50 years, the capacity will be replaced by new investments in gas-fired combined

Table 9.3 | Investments in conventional capacity. The investments are similar in both scenarios, thus showing only a small influence of CRMs in Switzerland's neighboring countries. In the EOM scenario, the total investment is slightly higher, although the first investments are made later.

	Gas Combined Cycle [MW]		Open Cycle Gas Turbine [MW]	
Years	EOM	CRM Policies	EOM	CRM Policies
2020-2024	–	–	–	800
2025-2029	1200	–	–	–
2030-2034	800	1200	–	–
2035-2039	400	–	–	–

cycle power plants up to a total capacity of 2.4 GW (see Table 9.3). However, if the nuclear power plants are operated for a longer period, this picture may change.

The increase in installed RES capacity in Switzerland is mainly caused by the growth in solar power plants, due to the input data. The installed wind capacity increases from 367 MW in 2020 to 2367 MW in 2050 and for solar from 650 MW in 2020 to 13 900 MW in 2050. As a result, the total generation capacity rises from over 21 GW in 2020 to over 36 GW in 2050 in the EOM scenario.

CRM Policies scenario

For the study of CRM market designs, availability factors of 6 % for wind and 1 % for PV were assumed at all hours. In particular in Italy, conventional power plants are considered with a 90 % availability in the CRM, and for the capacity market auction, an additional reserve of 3 % of the peak load is implemented. For France defined by Réseau de transport d'électricité [RTE] (2017), a security factor of 1.03 as well as capacity credits for wind (20 %) and solar (5 %) are applied for the first years. For Germany, the SR ('Kapazitätsreserve') allocates 5 GW. In all market areas, DSM (interruptible load) capacities in the amount of 2 % of the maximal peak load for a price of 700 EUR/MWh are assumed.

In the CRM Policies scenario, all model results are generated considering already implemented or proposed CRMs. Therefore, the introduction of the capacity markets in France and Italy leads to significantly higher capacities and to a more constant conventional capacity development in these countries compared to the EOM scenario (see Figure 9.7). In the scenario with CRMs, the increasing demand for flexible generation capacity is driven by the peak demand plus potential security margins, e.g., defined by the regulatory authority.

RES can have a mitigating effect on the rise of the conventional capacity demand caused by the CRMs. However, due to the fluctuating behavior of RES, they may only participate to a certain extent in the capacity market (or by reducing peak residual demand). This also depends on the respective design or parameterization of the CRMs. However, as a result of the capacity credits, the sum of the required and installed conventional capacity corresponds to almost peak demand in the overall market area due to the CRM configuration.

For illustration, Figure 9.7 shows the capacity development in Switzerland and in the neighboring countries. In Table 9.3, the investments in new power plants are listed. Investments are made purely in gas-fired power plants (2 GW). However, investments not only in CCGTs but also in OCGTs are part of the results. The OCGTs outperform CCGTs in terms of capital costs. Therefore, the agents choose the OCGTs if the power plant is mainly built to provide reserve or if the power plant is dispatched only for a small number of hours in the spot market with low average market prices.

9.3.3 Generation adequacy

The generation adequacy is illustrated here in the form of hours and expected volumes where the electricity spot market cannot be cleared normally. Section 9.3.3 summarizes and aggregates the number of hours in which the spot market in the model cannot generate a feasible market result with usual generation capacities. Hence, either immediately-switchable capacity is necessary for market clearing or the market

Table 9.4 | Usage of demand side management. Whereas in the EOM scenario all countries considered are dependent on DSM applications, their use is significantly reduced by the introduction of CRMs; in the case of Italy and France, DSM is no longer activated.

	Unit	CH	DE	FR	IT	AT
EOM scenario						
DSM usage	[h]	846	988	982	725	834
No market clearing	[h]	0	492	541	308	2
Expected load not served	[MWh]	0	5337	5470	3992	1127
CRM Policies scenario						
DSM usage	[h]	14	165	0	0	88
No market clearing	[h]	0	42	0	0	17
Expected load not served	[MWh]	0	1936	0	0	1042
DE 2 GW *SR sensitivity scenario*						
DSM usage	[h]	16	144	2	0	81
No market clearing	[h]	0	29	0	0	16
Expected load not served	[MW]	0	1855	0	0	1097

cannot be cleared due to insufficient supply ("No market clearing, therefore price is 3000 EUR/MWh (EPEX SPOT, 2018b)). However, this does not necessarily indicate black- or brownouts, because there is, for instance, still the available control reserve capacity. The availability of DSM potential is assumed to be 2 % of the peak demand in all market areas. Section 9.3.3 indicates the accumulated number of hours with the use of DSM or with no market clearing for both scenarios. Furthermore, the expected energy not covered in the case of a non-feasible market result in the spot market is specified in the same table.

In Switzerland, the lower installed generation capacity in the CRM Policies scenario does not increase the number of hours in which the market cannot be cleared or the hours when DSM is needed to clear the market successfully. On the contrary, the number of hours with DSM dispatch even falls due to higher flexible capacity in the neighboring countries compared to the EOM scenario. In the EOM scenario, the market can be cleared at all hours, which is caused by the use of DSM and the high

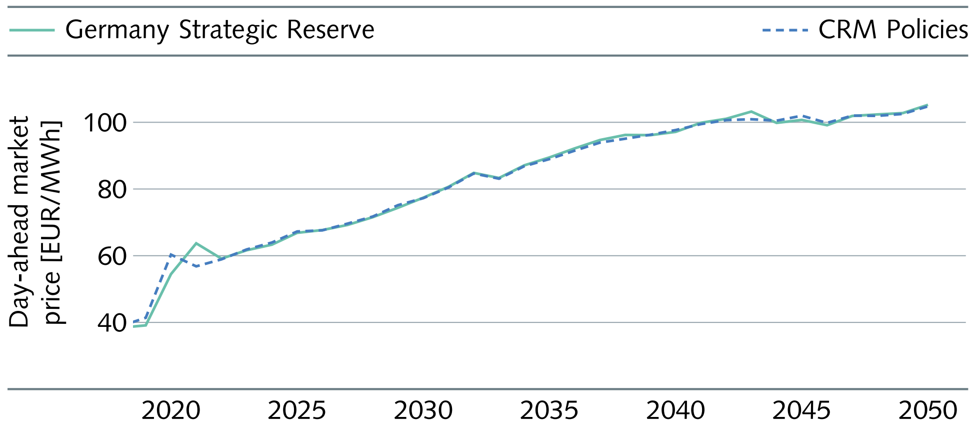

Figure 9.9 | DE strategic reserve sensitivity. Only marginal differences are identifiable between both price curves. In the years 2020 to 2022 in particular, a deviation in the prices is discernible, as the SR in Germany starts in 2020 and capacities are taken out of the market. Moreover, some years later (around 2044), there will be further slight differences in prices.

hydropower capacity. In the CRM Policies scenario, only Austria has many hours in which the market cannot be cleared.

Figure 9.8 shows the flexible capacities in Switzerland in the two scenarios. Due to the slightly lower market prices and the higher flexible capacities (stimulated by CRMs) in the neighboring countries France and Italy, the total installed capacity in Switzerland is lower in the CRM Policies scenario by 400 MW from 2030. However, this does not increase the number of hours, in which the market cannot be cleared, or the hours when DSM is needed to successfully clear the market, as more capacities from the neighboring market areas are available also for the Swiss market.

9.3.4 Sensitivity analysis for the size of the strategic reserve in Germany

In order to consider other possible developments, an additional scenario is added and the results are briefly presented in this chapter. In this scenario, the strategic reserve in Germany is reduced to 2 GW (instead of 5 GW), as the current regulation allocates a maximum of 2 GW until 2025, however, maximal 5 GW are legally permissible.

In the scenario, there is hardly any difference in the development of prices and capacities in Switzerland. It is necessary to compare the results of the model simulations with 2 GW SR in Germany (DE strategic reserve sensitivity) with those of the CRM Policies scenario, as no strategic reserve is used in the pure EOM scenario.

With regard to the prices shown in Figure 9.9, only marginal differences are identifiable. In the years 2020 to 2022 in particular, a deviation in the prices is discernible, as the SR in Germany starts in 2020 and capacities are taken out of the market. Moreover, some years later (around 2044), there will be further slight differences in prices.

These minor differences in prices do not affect capacities and incentivize investments in the scenario. At the beginning, compared to the CRM Policies scenario higher capacity in Germany, this does not lower the capacity in Switzerland, as rather old power plants are allocated to the SR, and old power plants leave the market sooner.

In 2021, the increase in prices in the DE Strategic reserve sensitivity scenario is caused by the fact that in the scenario with 5 GW SR (CRM Policies), investments are made promptly due to the higher capacity taken out of the market and thus the market price falls. In the DE Strategic reserve scenario, initially no investments are made, but therefore shortages occur in the market and the prices rise.

Section 9.3.3 shows the number of hours in which DSM is used and the number of hours in which the wholesale market cannot be cleared. According to these figures, no massive differences to the CRM Policies scenario arise. Thus, the number of hours in which Switzerland has to use DSM for market clearing increased by 2 to 16 as well as the hours in France also increased by 2, whereas the hours in Germany and Austria decreased. The increase in France and Switzerland is due to scarcity in the neighboring countries and therefore, more electricity had to be exported. The number of hours without market clearing in Switzerland, France, and Italy remains at 0. In Germany, the number drops to 29 (from 42 in the CRM Policies scenario). In Austria, the number of hours declines by 1 to 16. The decrease in the number of hours of DSM usage and no market clearing in Germany and Austria is mainly due to the fact that more capacity will be available in the years after 2020 and the market can therefore be cleared more often without any help of DSM. The expected energy not served is also declining slightly in Germany but rises slightly in Austria. In summary, this sensitivity confirms the results of the CRM Policies scenario.

9.4 Critical reflection

The scenario analyses presented in this chapter are carried out formulating own assumptions or using best available studies for the uncertain input parameters, such as the development of the electricity demand, prices for carbon certificates, and fuel prices for gas or coal. No market data are accessible for a time horizon up to 2050. This is why the EU Reference scenario (European Commission, 2016c) is taken as an input source for the investigation. However, this input data are only available in steps of 5 years, so that the intermediate years had to be linearly interpolated. Data about technological developments and trends in energy technologies (both conventional and RES) can only be found to a limited extent.

Further simplifications have been made with regard to the electrical grid. The domestic grid is not modeled, neither the transmission nor the distribution grid level, only the interconnector capacities are considered by using net transfer capacity (NTC) values. This means that no grid congestions within a country or other disturbances in the grid are taken into account, but they may play an important role in reality. However, as the study focuses on the balance between supply capacity and demand at the market area scale, the inner-market area bottlenecks play a minor role. In contrast, storage expansion, especially large-scale diffusion of battery storage, can significantly improve generation adequacy but has not been considered in this study. The selected approach follows the study by Prognos (2012) for Switzerland, which does not envisage any expansion of hydro storage facilities in Switzerland.

Furthermore, some own assumptions had to be made in the CRM modules, as not all market design details are available for all market areas. For instance, in the French capacity market, the used agent-based simulation model does not differentiate between the obligated parties regarding different demand curve patterns, e.g., for sectors or consumers. Beyond that, the participation of foreign power plants in CRMs is only considered by taking neighboring capacity shares into account in the security margin parameter. Therefore, future research should also focus on further design parameter variations and possible cross-border impacts of alternative designs.

9.5 Conclusions and policy implications

As generation adequacy is strongly dependent on investments in flexible generation capacity, it is monitored continuously with great scrutiny by regulators. Cross-border effects can strongly influence the investments in neighboring countries and thereby increase or decrease the level of domestic generation adequacy. Thus, it is essential to assess and anticipate these effects.

In this paper, changes in the market design of neighboring countries and, in particular, their effects on a small market area (asymmetric market constellation) are investigated taking the Swiss electricity market as an illustrative example. Switzerland is largely influenced by surrounding electricity markets and needs to analyze the political decisions regarding market design changes and to react to developments in the neighboring countries. The strength of this influence is studied with the help of an agent-based simulation model that is applied to two different scenarios describing possible developments with a time horizon until 2050. The long-term time horizon allows to analyze the generation adequacy not only for the current energy system with a comparably low share of intermittent renewables but also for a time period with very large shares of intermittent sources in the energy system that may not be available when they are needed in peak demand hours. The first scenario assumes energy-only markets (EOMs) in all regarded countries, whereas the second one considers implemented capacity remuneration mechanisms (CRMs) in the neighboring countries, but not in the Swiss market.

In general, the model results indicate a strong price increase in the Central Western European electricity markets, mainly due to rising carbon certificate prices and increasing demand. However, the price increase in the CRM Policies scenario is about 27 EUR/MWh higher in the long term. This is caused by the introduction of national CRMs with high targets for domestic generation adequacy, which lead to overall higher installed capacities in the entire coupled market area. Contrary, in the EOMs scenario the capacities are scarce resulting in price peaks.

Regarding the cross-border effects on the country without a CRM, in this case Switzerland, it is shown that higher capacities in the neighboring countries lead to less domestic investments. Therefore, in the CRM Policies scenario, the Swiss market can rely on higher imports from the neighboring countries. Hence, Switzerland remains dependent on neighboring countries, although it has a very limited influence on their market design. However, it also turned out that sufficient capacity is available to serve the electricity demand in each time step in both scenarios. The reasons for that are large interconnector capacities and high hydropower capacity in Switzerland. This means that although there is an influence on prices, the generation adequacy in Switzerland is not adversely affected by market design changes in neighboring countries.

Regarding the operational revenues of hydropower plants in the Swiss market, it can be concluded that, as this mainly depends on the development of wholesale electricity prices, the situation is more favorable in the EOMs scenario than in the CRMs Policies scenario. The EOMs scenario produces higher wholesale prices reaching an average annual price of 120 EUR/MWh in the long term. However, with low operating costs for hydropower and increasing wholesale electricity prices, it is very likely that the hydropower plants can be operated profitable independently from the CRM policies in the neighboring countries in the future. For this reason and due to the fact that generation adequacy is ensured, a change of the Swiss market design is currently not required in any of the investigated scenarios.

9.6 Additional results and model details

In the following, additional details to the information already presented in Section 9.2 are provided.

9.6.1 Bidding strategies for hydro storage power plants

In Switzerland, hydropower accounts for the largest share of electricity generation (Swiss Federal Office of Energy, 2018b). Analyses of the Swiss electricity market require an adequate representation of hydropower plants in an electricity market model. Approximately 16.1 GW of hydropower generation capacity (with a peak demand in 2017 of 10.9 GW (Swiss Federal Office of Energy, 2018c)) and a total storage capacity of 8.8 TWh (with 62.9 TWh total electricity consumption in 2017 (Swiss Federal Office of Energy, 2018c), see Figure 9.10) are available. The hydropower generation capacity (including power plants under construction) is divided into 4.6 GW of run-of-river, 3.1 GW of pumped storage plants and 8.3 GW of seasonal hydro storage plants (Swiss Federal Office of Energy, 2018d).

To determine a schedule that maximizes the revenue of seasonal hydropower storages is a complex problem for which different approaches with varying degrees of detail exist (Hongling et al., 2008). In contrast to the operation of a thermal power plant that is based on its variable costs, arising mainly from the use of fossil fuels and emission allowances, for storage power plants, the operation depends on opportunity costs, which have to be determined first. As these costs depend on the future development of several uncertain factors, such as weather-dependent inflows, but also on demand and fuel costs (Yakowitz, 1982), both a short-term (days to

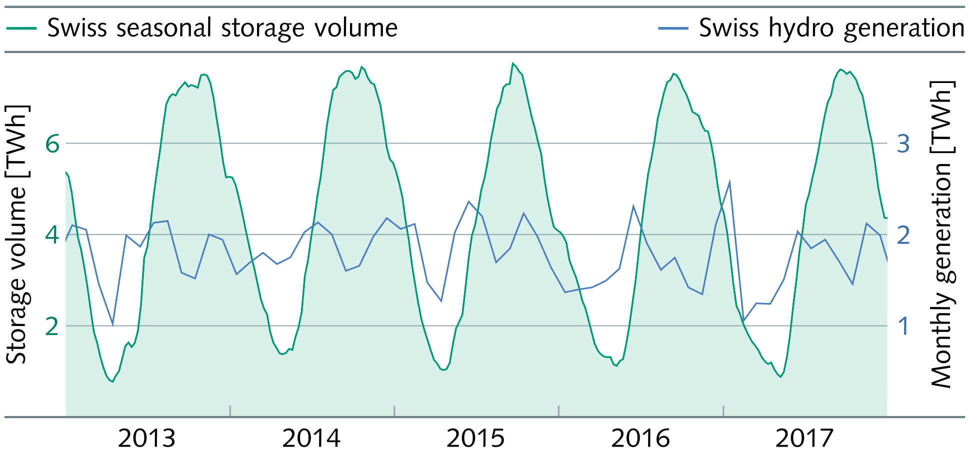

Figure 9.10 | Historical and simulated storage volumes. In contrast to the storage level, which has a clear annual profile, the generation of hydropower does not exhibit a pronounced recurrent pattern. This suggests that the monthly generation through water turbines excluding pumped storage lies within certain limits, but reacts dynamically to market developments.

months) and a medium-term time (one to five years) horizon must be considered (Steeger et al., 2014).

Thus, it can be assumed that hydropower does not act as a pure price-taker, but actively influences market prices, which further complicates the determination of an optimal schedule. The combination of the long considered periods of time, the multitude of influencing variables, as well as the fact that the optimal schedule must be determined for every simulated day, lead to the fact that an implementation would exorbitantly increase the computing time of the model. Therefore, different approaches to include the hydropower technologies have been applied.

The run-of-river power plants were integrated into the model based on a static generation profile (Swiss Federal Office of Energy (2017) data used from the year 2015) due to the more or less regular values for monthly generation and inflexible production over the years. Meanwhile, the pumped storage plants are modeled as described by (Fraunholz et al., 2017) for an available storage volume of 10 % of the total volume according to Swiss Federal Office of Energy (2018c).

Due to its transparency, a linear regression approach is chosen in order to model the seasonal hydropower in Switzerland. This custom heuristic, in which an optimal use cannot be guaranteed, but which resembles the historical generation, takes into account the simulated developments, and at the same time only marginally extends the computing time. For this purpose, the hourly historical production time series of seasonal hydro storage power plants from ENTSO-E (2018b) for the years 2015 to 2017 are used for this regression. The regression was applied for each season of the year $t \mapsto s \in S$:

$$\begin{aligned} hydroGen_t = & \beta_s^0 + \sum_m \left(\beta_{m,s}^{load} load_{m,t} + \beta_{m,s}^{RES} RES_{m,t}\right) \\ & + \sum_{m \neq CH} \beta_{m,s}^{NE} netExchange_{CH \rightarrow m,t} \\ & + \sum_{i=1}^{23} \beta_s^i hour_t \qquad \forall t \qquad (9.3) \\ & + \beta_{CH,s}^{Storage} V \\ & + \epsilon_t \end{aligned}$$

with

Parameters

$load_{m,t}$	:	Normalized physical load
$RES_{m,t}$	:	Normalized renewable feed-in
$netExchange_{CH \rightarrow m,t}$	:	Net electricity exchange between Switzerland and market m
$hour_t$	:	Dummy for the hour of the day
day_t	:	Dummy for the type of day
V	:	Storage volume in Switzerland

Sets

$s \subset S$	:	Season of the year
$m \in \{AT, CH, DE, FR, IT\}$	:	Markets

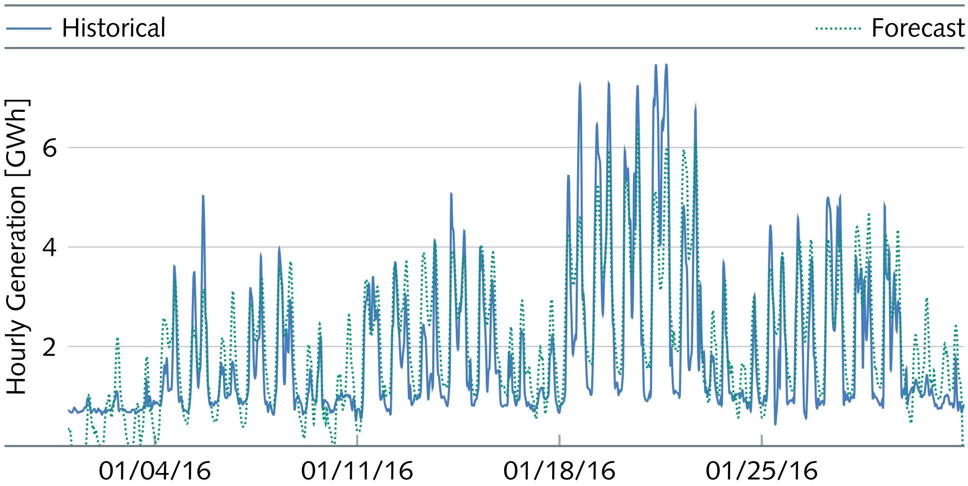

Figure 9.11 | Historical and fitted generation of seasonal hydro storages. The values for January 2016 show a similar pattern, although the positive peaks in the historical values appear more pronounced and, vice versa, the negative peaks in the simulated values.

The following influencing factors are examined with the assessment of the regression: Demand, RES feed-in, weekday or weekend, exchange flows with neighboring market areas, storage level and hour of the day. Coefficients for these factors are individually estimated for each season. To account for the increasing capacity of RES, normalized feed-in values (normalized to the total annual production) are used for the variable RES feed-in. Equation (9.3) describes the regression model. Table 9.6 documents the individual regression coefficients for each season.

The developed regression model and its coefficients are integrated into the agent-based model. Based on the regression model, the hourly operation of the seasonal hydropower plants is calculated. In addition, the storage levels are tracked at any time and in the event of overflow or underrun, the operation is adjusted accordingly. Taken from the model results, Figure 9.11 shows the hourly operation in winter simulated with the regression model compared with the real operation. As the values of the regression can also become negative or exceed the possible use, two more limits are introduced:

Table 9.5 | Validation of the agent-based model. The compared day-ahead wholesale historical and simulated prices are similar in both regarded scenarios; thus showing the suitability of the applied model. *Source:* EPEX SPOT (2018b).

[EUR/MWh]	2015		2016	
	hist.	sim.	hist.	sim.
Switzerland	40.30	43.41	37.88	38.29
Germany/Austria	31.63	43.51	28.98	38.48
France	38.48	39.07	36.75	34.17
Italy-North*	52.71	42.64	42.67	38.01

* The national average price (PUN) in Italy was 52.31 EUR/MWh in 2015 and 42.78 EUR/MWh in 2016.

$$hydroGen_t = \min\left\{hydroGen \max\left\{0, hydroGen_t\right\}\right\} \tag{9.4}$$

In addition, further bids will be made to ensure that all the required capacity is available when needed. These are offered at a high price in the market (above the most expensive thermal power plant) so that they are only used in particularly scarce situations and at the same time to ensure that annual generation does not become too high.

9.6.2 Validation

To verify the results, a short validation based on historical prices is carried out in advance. Table 9.5 shows the comparison of real electricity wholesale prices, of the years 2015 and 2016 (EPEX SPOT, 2018b), and the prices that are calculated in the simulation. In some cases, there are larger deviations. Concerning the German price deviation, it has to be mentioned that several market areas around Germany, e.g., Denmark, Poland, have not yet explicitly been modeled. Although the exchange flows with these markets are considered via static exchange, only the hourly volume effects, but not price effects of these flows are taken into account. Calculations with all neighboring market areas of Germany show that the mean value of deviations was below 2 EUR/MWh for Germany and Austria in the years 2015 and 2016. Furthermore, the carbon certificate prices in this study are derived from the EU Reference Scenario (European Commission, 2016c), but in reality, the carbon certificate prices were lower in these years, which also explains some of the higher electricity prices in the simulation. The error between simulated and historical series is quite small for the Swiss and French electricity prices. In general, the price validation delivers sufficiently good results except for Italy. The main reason for the deviation in Italy is that there is no internal splitting of Italy into different price zones in the model as it is the case in reality. Therefore, no domestic grid restrictions in Italy are taken into account that would shorten the market in the different zones and lead to higher prices in the model. Higher prices in the different zones in Italy lead to a higher average than in the case of considering Italy as a unique market zone.

Table 9.6 | Regression coefficients. A significant factor for the operation of seasonal storage is the demand in neighboring countries, besides there is a daily pattern with a peak at noon. Results for the different seasons, however, can differ considerably.

	Spring		Summer		Autumn		Winter	
	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value	Estimate	p-Value
β^0	−3055	0.00	−2590	0.00	−5492	0.00	−4414	0.00
$\beta^{Storage}_{CH}$	0	0.12	0	0.81	0	0.00	0	0.00
β^{load}_{CH}	−167	0.52	804	0.02	−1277	0.00	1215	0.00
β^{load}_{IT}	1791	0.00	1008	0.00	4910	0.00	3698	0.00
β^{load}_{AT}	−50	0.87	1524	0.00	−911	0.00	−1883	0.00
β^{load}_{FR}	287	0.18	2646	0.00	3117	0.00	2426	0.00
β^{load}_{CH}	4499	0.00	1991	0.00	2292	0.00	2668	0.00
β^{RES}_{DE}	−117	0.00	−1022	0.00	−247	0.00	63	0.05
β^{RES}_{IT}	404	0.00	98	0.09	113	0.03	−95	0.19
β^{RES}_{AT}	−116	0.10	16	0.79	−360	0.00	−403	0.00
β^{RES}_{FR}	−648	0.00	1084	0.00	−349	0.00	−396	0.00
β^{RES}_{CH}	165	0.10	−1276	0.00	417	0.00	−637	0.02
β^{day}	−138	0.00	−169	0.00	−133	0.00	−33	0.40
β^1	−4	0.96	96	0.23	91	0.24	−48	0.58
β^2	−35	0.64	70	0.39	146	0.06	−6	0.94
β^3	−74	0.32	−66	0.43	57	0.46	−1	1.00
β^4	−177	0.02	−361	0.00	−292	0.00	−152	0.09
β^5	−230	0.01	−442	0.00	−503	0.00	−530	0.00
β^6	−7	0.94	168	0.12	−404	0.00	−617	0.00
β^7	−10	0.92	496	0.00	−285	0.00	−489	0.00
β^8	−226	0.03	302	0.01	−368	0.00	−442	0.00
β^9	−546	0.00	−19	0.88	−506	0.00	−433	0.00
β^{10}	−679	0.00	−105	0.39	−466	0.00	−623	0.00
β^{11}	−744	0.00	−261	0.03	−500	0.00	−619	0.00
β^{12}	−871	0.00	−433	0.00	−715	0.00	−784	0.00
β^{13}	−898	0.00	−521	0.00	−791	0.00	−877	0.00
β^{14}	−885	0.00	−646	0.00	−849	0.00	−711	0.00
β^{15}	−822	0.00	−762	0.00	−862	0.00	−667	0.00
β^{16}_s	−669	0.00	−632	0.00	−993	0.00	−794	0.00
β^{17}_s	−466	0.00	−138	0.18	−685	0.00	−607	0.00
β^{18}_s	−31	0.73	399	0.00	−60	0.55	−382	0.00
β^{19}_s	201	0.02	417	0.00	−23	0.80	−303	0.00
β^{20}_s	102	0.21	180	0.05	−370	0.00	−490	0.00
β^{21}_s	−27	0.73	226	0.01	−339	0.00	−495	0.00
β^{22}_s	−11	0.89	−51	0.54	−243	0.00	−368	0.00
β^{23}_s	−2	0.97	17	0.83	−98	0.20	−197	0.03
$\beta^{NE}_{DE,s}$	−0	0.00	−0	0.00	−0	0.00	−0	0.00
$\beta^{NE}_{AT,s}$	−1	0.00	−0	0.23	−1	0.00	−0	0.00
$\beta^{NE}_{FR,s}$	−0	0.00	−0	0.00	−0	0.00	−0	0.00
$\beta^{NE}_{IT,s}$	−0	0.00	−0	0.00	−0	0.00	−0	0.00

Chapter 10

Conclusions and outlook

The research carried out in this dissertation provides several scientific contributions. On the one hand, the current knowledge of capacity remuneration mechanisms is structured, summarized, and expanded in different areas. On the other hand, a methodological approach is developed that enables the analysis of electricity markets taking into account real-world conditions via a detailed agent-based model.

Initially, capacity remuneration mechanisms were primarily used in the US. In recent years their use has also been increasingly discussed in Europe, where some countries, e.g., France and the UK, have already introduced them, and in other countries, for instance, Germany and Italy, the implementation is still in process. In academia, capacity remuneration mechanisms for electricity markets have been studied since the first decade of the 20th century (e.g., Cramton and Stoft, 2005; Joskow and Tirole, 2007; Oren, 2000; Vázquez et al., 2002). While interest in capacity remuneration mechanisms has remained largely constant for some time, recent developments have led to increased research activities. Nevertheless, many questions remain unanswered or only partially answered, for example: How do the different capacity remuneration mechanisms perform in terms of efficiency and effectiveness? How does the increased penetration of renewable energies affect the necessity and the design of capacity remuneration mechanisms? What are the cross-border effects between different national market designs and what complications arise from uncoordinated national policies in real-world markets?

In their search for answers to the aforementioned questions, researchers could draw on a large pool of existing work that examined the long-term development of electricity systems by applying various model types but did not explicitly consider capacity remuneration mechanisms (Bazmi and Zahedi, 2011; Connolly et al., 2010; Foley et al., 2010; Guerci et al., 2010; Möst and Keles, 2010; Ventosa et al., 2005; Weidlich and Veit, 2008). Therefore, existing approaches had to be extended for the evaluation of capacity remuneration mechanisms[1]; however, simplifications regarding the techno-economic characteristics of electricity system were frequently made limiting the explanatory power and making it difficult to transfer results to real-world applications. For instance, analytical models require strong simplifications to obtain a feasible solution. In Briggs and Kleit (2013) as well as Joskow and Tirole (2007), only two different power plant types were regarded without start-up costs or start-up times. In addition, system dynamics models were applied (e.g., Ochoa and Gore, 2015; Petitet et al., 2017), but typically only a simplified presentation of techno-economic restrictions was implemented, and interactions between the individual market participants were neglected. Optimization models, as for example used by Levin and Botterud (2015) or Neuhoff et al. (2016), represent the most widespread approach. On the one hand, these models are able to take into account a multitude of technical constraints. On the other hand, optimization models are limited in the representation of different capacity remuneration mechanisms and typically adopt a pre-liberalization perspective in which all decisions are taken by a central authority.

In this regard, agent-based models present a flexible and capable approach that allows to model markets and economies as complex adaptive systems taking into account interactions of market participants as well as human learning (Farmer and Foley, 2009). Nevertheless, with the exception of Bhagwat (2016), the agent-based modeling approach is not yet widely used for research of capacity remuneration mechanisms. To date, there are still no studies of real-world electricity markets that

[1] A detailed survey of the current research is presented in Chapter 5.

adequately reflect the various interconnected markets, e.g., balancing and day-ahead markets, take into account the essential techno-economic details of power plants and implement the perspective of market participants confronted with investment decisions under uncertainty. Thus, this dissertation aims to broaden the current knowledge of capacity remuneration mechanisms by applying an agent-based model to investigate the development of the electricity market under imperfect conditions and uncertainties taking into account the expansion of intermittent renewable energies. In this way, both the fundamental economic and technical aspects of electricity markets can be adequately addressed.

10.1 Conclusions

The objective of this dissertation is to gain a better understanding of the need, design, and effects of capacity remuneration mechanisms for electricity markets in transition. To this end, the first chapters shed light on the peculiar characteristics of electricity markets and examine the fundamental interrelationships by applying different models in a coherent assessment. The main analyses carried out can be summarized in answers to the following central research questions:

What are the principal drivers for the price decline in European wholesale electricity markets and does their influence necessitate additional investment incentives in thermal capacities? Based on different numerical models, the obtained results demonstrate that fuel and carbon prices still have a dominating impact on wholesale electricity prices and the widespread opinion that the merit order effect of renewables is the sole reason for the low prices faced today at wholesale markets has to be at least partly rejected. In a ceteris paribus analysis, the total price effect[2] of photovoltaics

[2] It should be noted at this point that although the ceteris paribus analysis offers a good breakdown of the individual factors, their absolute value offers room for misinterpretations. One of the reasons is that only one factor is changed at a time. For example, if the overall price effect of renewable energies is determined, it is assumed that no renewable energies would exist and no further thermal capacities

and wind since their market introduction in Germany equals 14 to 15 EUR/MWh and is indeed a substantial effect. However, the additional price effect between 2011 and 2015 is contributing only in the range of 5.40 to 6.80 EUR/MWh to the price decrease of almost 20 EUR/MWh, which roughly equals the sole effect of the coal price decline. This suggests that recent price developments on the electricity market are strongly influenced by other markets, and new dynamics could lead to a partial recovery of electricity prices. For example, a scenario analysis for 2020 shows that a modern gas-fired power plant can generate enough revenue to cover variable and operational fixed costs if coal and carbon prices recover to 2011 levels, partly due to its lower costs for emission certificates. In this situation, the prices are high enough to achieve a slightly positive annual return. Even though this could prove to be sufficient to keep existing gas-based capacity in the market, no new investments would be incentivized. Nevertheless, the development of other parameters, such as surplus capacities in the electricity market, also plays a key role in the recovery of electricity prices and has a significant influence on investors' decisions. Therefore, the necessity of additional investment incentives for thermal capacities in the short term is currently not clearly evident.

What are the associated benefits and challenges in implementing a capacity remuneration mechanism? The major advantage of capacity remuneration mechanisms is that they are able to effectively reduce or even to solve different problems of existing markets and thereby improve generation adequacy. For example, fluctuations caused by investment cycles can be dampened and, thereby, extreme scarcity events can be prevented. In addition, market developments are more predictable by avoiding deviations from the long-term optimum caused by risk-averse decision-makers. Also, the adverse effects of the abuse of market power can be mitigated, and some mechanisms, for example, a forward capacity market, are able to solve the missing money problem caused by regulatory price limits. However, determining the optimal market

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would be added as replacements, even if they were urgently needed.

design remains a complex challenge. The adequate design for a market depends on a variety of factors such as the existing capacity mix and demand characteristics. Thus, no general advantageousness of single mechanisms could be determined yet. Furthermore, extreme diligence must be exercised when adapting the market design, as the implementation of a capacity remuneration mechanism can lead to market distortions, e.g., through cross-border effects. Even though the cross-border impacts are complex and sometimes conflicting, there seems to be a consensus that a one-sided implementation leads to negative spillover effects on a neighboring market without any capacity remuneration mechanism. Thereby the pressure increases to either introduce an own mechanism or to rely on a coordinated approach. In addition, the value of flexible resources, which is closely related to volatile prices, is reduced in the presence of a capacity remuneration mechanism, and as a result, their expansion is largely left in the hands of the regulator.

Is the current market design in Germany sufficient to guarantee generation adequacy and are the proposed capacity remuneration mechanisms both effective and efficient? The quantitative analysis with an agent-based model shows that the existing German market design leads to a market equilibrium in the short and medium term as generation adequacy is ensured, i.e., the supply side can deliver the required capacity to meet the electricity demand at all times. However, this can be mainly attributed to the growing coupling of European electricity markets and existing surplus capacities, which mainly stem from the period before liberalization. Furthermore, it is worth mentioning that these results also rely on the condition that at least a moderate level of 2 GW of sheddable loads can be activated during peak load situations. In the long term beyond 2030, the results indicate that generation adequacy cannot be fully guaranteed without additional capacity remuneration mechanisms. The electricity demand cannot be completely met in several situations by the available capacity in the day-ahead market, and at least spinning and non-spinning reserve power have to be dispatched to avoid brownouts. Due to uncertain cash flows and difficult to predict and seldom occurring extreme price peaks, only insufficient investments are made. The functionality of the EOM can be improved, if the available capacity of sheddable loads is increased to about 8 GW or if the at time envisaged capacity reserve of 5 GW[3] were to be implemented. Such a national capacity reserve is able to provide long-term generation adequacy and would mainly consist of existing lignite, gas and oil-fired power plants, but rarely of newly built capacities.

Which cross-border effects arise from capacity remuneration mechanisms and is the introduction of a national mechanism required in order to mitigate severe adverse consequences, for example in case of the Swiss market? In the case of a smaller country neighbored by large markets (asymmetrical market areas), the impact of cross-border effects from capacity remuneration mechanisms is more clearly evident. Therefore, the Swiss electricity market, which is tightly connected to its larger neighboring markets of France, Italy, and Germany, serves as a useful example to analyze possible cross-border effects. In a case study, two scenarios are regarded: In one scenario, all market designs are represented according to the current legislation. In a second scenario, a so-called energy-only market is assumed in countries surrounding Switzerland. The results show a clear cross-border impact, as wholesale electricity prices are highly dependent on the chosen market design. Although the introduction of capacity mechanisms is a disadvantage for foreign generators, as they cannot participate in the same way as local ones, the planned market design changes in Switzerland's neighboring countries do not necessarily have a negative impact on national investments and a local capacity remuneration mechanism does not seem to be required to secure generation adequacy. However, this result is strongly influenced by the level of available storage capacities, in the case of Switzerland, ample hydropower storage facilities, which are used to cover peak national demand when foreign generation capacity is unavailable or used domestically.

[3] After initially envisaging the implementation of a capacity reserve of up to 5 GW, the volume was reduced to 2 GW, as additional lignite capacities in standby mode amounting to 2.7 GW are available, which can also be dispatched in scarcity situations (European Commission, 2017b).

10.2 Limitations

At this part, the existing limitations of the analyses carried out are addressed on a general level and specific restrictions are dealt with afterward. In this work, different modeling approaches are used for a variety of topics demonstrating the wide range of current electricity market models. Although a large number of improvements and extensions to economic models have been achieved in recent years, it should be noted that there are still some limitations that, without claiming completeness, can be categorized as follows: First, the inability to represent real word systems. Second, the dependence on valid input data. Third, the role of critical assumptions and structural distortions.

Inability to fully represent real-world systems

"All models are wrong," claims the well-known statistician George Box (1976), "but some are useful." The main intention of this aphorism is to point out that a model always includes simplifications and approximations and never reflects all of reality (Burnham and Anderson, 2002). In the context of this work, different model boundaries are drawn in terms of both the spatial resolution and the market elements under consideration. While the assumptions and aspects considered are of decisive importance for the results, real-world aspects, which have been neglected in the analysis, can be of equal importance. The model is also limited to certain countries of the European market and, for example, the Northern Europe region has been neglected. Dynamic external reactions in scarcity situations can therefore not be taken into account, leading to a possible underestimation of foreign capacities. In addition, the results of the analysis are each based on a representative weather year, which could have a significant influence on the question of generation adequacy. In addition, the EU-ETS, which has a considerable influence on the development of the electricity market, was not implemented endogenously, so that no interdependencies can be analyzed. However, as it can only be hypothesized in what way the disregarded elements influence the results with diverging effects on the scenarios considered, all results must be interpreted in the context of the applied model. Furthermore, technological disruptions, possibly the effect of the blockchain technology, are difficult to predict and can only be modeled within certain limits, but may have a decisive influence on future developments (Qudrat-Ullah, 2015).

Dependence on valid data

"Garbage in, garbage out" is a principle in computer science, which refers to the fact that computers cannot think for themselves, and that incorrect entries inevitably lead to incorrect results (Schneider and Gersting, 2018). Also for the analyses carried out in this dissertation, in particular when trying to replicate and analyze historical results, valid data is essential. Although extensive data sets from reliable sources, which have already proven useful in previous analyses, could be used, important parameters remain subject to uncertainty. For example, the techno-economic parameters, i.e., the efficiency, minimum load, start-up and downtimes, of hundreds of power plant units in the market areas under consideration are required for the models, but for the vast majority of the units, these values can only be estimated. Even if this uncertainty has been addressed by analyzing a broad range of different values, not every parameter combination could be tested and, furthermore, the future development of these values can only be estimated. Hence, there exists no definitive certainty about the correct input data.

Another essential aspect is the behavior of the agents considered in the model. However, especially for investment decisions but also for strategic bidding in scarcity situations, which form the basis for the investigation of generation adequacy and the effectiveness of capacity measures, the behavior of agents is exceptionally difficult to validate. Whereas it is assumed that all agents are homogeneous and act risk neutral, in reality, different types of investors exists, such as utilities, banks or renewable energy cooperatives, with partly deviating risk profiles (Gross et al., 2010; Herbes et al., 2017). If the majority of investors continues to behave risk-averse in the future, the investment volumes in the case-study may have been overestimated.

Assumptions and scenarios

Although scenarios are not intended to make predictions about the future, they provide guidance by quantifying possible developments under alternative circumstances. For example, part of the results on the analysis of generation adequacy achieved depend heavily on the availability of interruptible loads. Although the consumption of households is still considered generally inelastic, this situation could change more drastically than in the scenarios considered. Public appeals, such as the tweet by the French Interior Minister during a cold period in February 2018 (Ministère de l'Intérieur, 2017), could offer additional flexibility in extreme situations. However, such measures have not been regarded in this work. In addition, the more stringent climate targets and the imminent phase-out of coal in Germany can have a major impact on the results of the case studies carried out. However, this was not taken into account due to the different framework conditions at the time the case studies were carried out. As a result, in Germany, an earlier introduction of a capacity market could be favorable.

10.3 Recommendations

In the following sections, first, the recommendations for action for political decision-makers are presented followed by different suggestions for researchers to address unresolved research questions.

10.3.1 Recommendations for policy makers

While economists continue to discuss the question of the optimal market design for the electricity sector, policy makers must already position themselves in the face of remaining uncertainties regarding future market and technological developments. The following paragraphs are intended to contribute to making an informed decision and at the same time help to further improve electricity market design.

The necessity and effects of capacity renumeration mechanisms

One major advantage of capacity remuneration mechanisms is that they are able to effectively reduce or even to solve different problems of existing energy-only markets. For example, as shown in the case studies carried out, fluctuations caused by investment cycles can be dampened—even though usually not fully abolished—and, thereby, extreme scarcity events can be prevented. However, the implementation of a capacity remuneration mechanism can lead to market distortions, e.g., through cross-border effects. This confirms the importance of coordinating national mechanisms. Results from the literature show that a one-sided implementation of a capacity remuneration mechanism can lead to negative spillover effects on a neighboring market without a capacity remuneration mechanism. However, the example of Switzerland shows that these effects can be mitigated by expanded interconnection capacities and high storage capacities.

Determining the optimal market design, however, remains an ongoing challenge. As the adequate design depends on a variety of factors such as the existing capacity mix and demand characteristics, no general advantageousness of single mechanisms could be determined so far. For example, in order to increase generation adequacy in the short term, a strategic reserve is well suited, but it also leads to inefficiencies. Thus, in case of persistent concerns about generation adequacy, other mechanisms are advantageous.

Increasing demand response

In order to avoid inefficiencies in the energy-only market due to the exercise of market power, price caps have been introduced, in the knowledge that these can lead to underinvestment and reduce welfare (Fabra, 2018). To counteract and mitigate the consequences of price caps, capacity remuneration mechanisms aim to stimulate new investments. However, the underlying problem—namely the inelastic demand, which is a prerequisite for the exercise of market power—could also be addressed in an alternative way, i.e., by increasing demand flexibility. While the widespread equipping of all consumers with smart meters involves high costs and brings about new challenges, e.g., establish a reliable and secure operation, this seems to be without a viable alternative in view of the increasingly fluctuating generation (Zhou and Brown, 2017). Even if a capacity remuneration mechanism is introduced, as the results in the case studies carried out in this dissertation show, demand response is able to significantly reduce the amount of the required conventional capacity.

Determining a reliability target

In the energy trilemma of sustainability, affordability, and reliability, politicians attach overriding importance to reliability (Newbery, 2016a). In view of its prominent role, reliability should be determined and evaluated according to transparent criteria. For many European electricity systems, the LOLE is applied, for which a target value of 1 day in 10 years—corresponding to a value of 3 hours per year—should not be exceeded. However, this standard, which dates back to the 1950s, has been criticized as arbitrary and too strict to be economically optimal (Cramton and Stoft, 2006). In addition, there apparently exists a difference between the controlled shutdown for a modest number of consumers and the loss of load for all the connected appliances across the industrial, commercial, as well as private sector. Thus, applying a different measure, for example, the unserved energy measured in MWh/year, seems to be more reasonable (Lueken et al., 2016).

Reducing regulatory uncertainty

Whenever the future state of regulation is uncertain, the complexity for affected decision makers increases. This is particularly relevant for the possible introduction of a capacity remuneration mechanism, as, on the one hand, there is uncertainty about the possible design of the mechanism, and on the other hand, incremental adjustments are often made—for example, in the capacity market in the United Kingdom (Bhagwat et al., 2016b)—that can affect the profitability of investments. In the energy-only market, however, the question arises whether a regulator can withstand public pressure if very high prices occur over an extended period or whether strict price limits are introduced. For example, on January 5, 2018, the German Federal Network Agency (BNetzA) capped the energy price for balancing energy at 9999 EUR/MWh motivated by the one-off occurrence of an energy price peak of 77 777 EUR/MWh, on October 17, 2017 (BNetzA, 2018a). However, regulatory uncertainty can be detrimental to investments, as decision-makers tend to postpone decisions and make few changes to the status quo (Fleten et al., 2017).

10.3.2 Recommendations for future research

Based on the research conducted and in particular on the research not conducted in this dissertation, several research proposals are presented. The following four paragraphs are intended to further refine the understanding of capacity remuneration mechanisms, whereas the last two paragraphs aim at improving the capability of agent-based electricity market models.

Firm capacity of intermittent renewable energy

When analyzing the long-term generation adequacy and the need for capacity remuneration mechanisms under the increasing influence of the weather-dependent renewable energy sources, it becomes increasingly important to assess the effects of the stochastic nature of weather adequately. In order to determine the need for thermal capacity of an electricity system, first, it is necessary to assess the firm capacity each renewable technology can provide and, depending on the spatial distribution, what intertemporal dependencies exist. For example, Patlakas et al. (2017) find that low wind speed events of 3 meters/second can last up to 4 to 5 days in the open waters of the North Sea and up to 10 days nearshore—in specific cases even longer periods are possible. Therefore, it is crucial to understand how the future electricity generation of wind power is distributed, e.g., in Germany, low wind speeds are more frequent in summer when the electricity demand is typically lower. In summer, however, the feed-in from photovoltaics tends to be higher but lower when the peak load occurs on cold days in winter. Therefore, an integrated approach is indispensable to answer the open question to what extent these extreme weather events can be compensated in the national as well as the European context and what level of storage capacities is required (Grams et al., 2017).

Impact and value of flexibility options

Electrical energy storages, such as battery or compressed air energy storages, make it possible to store energy in a certain state and convert it into electrical energy when required. Therefore, storage technologies have enormous potential to meet the challenges of intermittent renewable energies, which are characterized by significant daily and seasonal variations, as these intermittent electricity sources can be backed up, stabilized or smoothed (Luo et al., 2015). In addition, demand response offers a wide range of potential benefits for system operation and market efficiency by promoting the interaction and responsiveness of the customers, i.e., residential households or the energy-intensive industry (Siano, 2014). These advances shape the development of the current energy system, and, in the short term, more attention needs to be paid to how these resources can be efficiently integrated into capacity remuneration mechanisms (Byers et al., 2018). Furthermore, in the long term, the need for thermal power plants to ensure generation adequacy could be reduced as demand response further increases and energy storage capacities further grow. In this process, also the need for capacity remuneration mechanisms could diminish. First tentative results indicate that demand response and energy storages may achieve an equal improvement of generation adequacy as capacity remuneration mechanisms but do so at lower costs (Khan et al., 2018). However, there is still a need for research on the interaction of flexibility options and capacity remuneration mechanisms in different, ideally more general settings and on whether flexibility options can eliminate the need for capacity mechanisms.

Prosumer era and smart grids

The so-called prosumer, with the ability to generate and store electricity as well as to interact with other prosumers, is gradually superseding the traditional power consumer (Grijalva and Tariq, 2011). With the increase in the number of prosumers, today's electricity sector will change dramatically in the coming decades. This, on the one hand, offers opportunities to reduce greenhouse gas emissions, but, on the other hand, brings forth risks that need to be identified and addressed. For example, prosumers can participate in peer-to-peer energy trading in a microgrid, which has already been the subject of a number of pilot studies (Zhang et al., 2018), and is facilitated by the fact that local authorities are striving for energy self-sufficiency (Engelken et al., 2016). However, these partial disruptive developments are not sufficiently addressed in current models as the existing analyses of capacity remuneration mechanisms and generation adequacy typically either neglect the actors' perspective or limit it by regarding only a few central actors. The implementation of large-scale, decentralized markets still requires a great effort on the part of researchers, suppliers, and policy makers if they are to be implemented further (Parag and Sovacool, 2016). Especially for modelers, this presents the great challenge of coping with the growing complexity of models, which results from the increased number of actors and the more detailed presentation of human behavior (Pfenninger et al., 2014). Yet, these challenges need to be addressed to examine how prosumers and decentralized markets may influence the need for capacity remuneration mechanisms and whether major regulatory intervention may even become superfluous.

Coupling of agent-based simulation with optimization techniques

The complexity of energy systems continues to grow as they become more decentralized, rely on multiple diverse energy sources and are more tightly interconnected. This entails several risks and the realization that some of the current models might not be capable of dealing with the emerging challenges (Pfenninger et al., 2014). Agent-based models have proven their ability to capture the interactions between agents and simulate the emergent behavior resulting from these interactions (Tesfatsion, 2006). However, it is an increasing challenge to model the multifaceted decisions of market participants with plain algorithms and at the same time fulfill all relevant constraints. A promising approach is to rely on optimization tools where these problems can be elegantly expressed, however, often only be resolved with brute computation power (Papavasiliou et al., 2015). However, the growing computing resources should facilitate the transition from algorithms to optimization methods. For this dissertation, for example, the cross-border exchange has been formulated as an optimization problem to maximize economic welfare. For the use of daily and seasonal storage systems, it is also increasingly relevant to develop optimal bidding strategies considering the bids impact on the market price (Steeger et al., 2014). A more in-depth model coupling on further levels would also allow comparing wholesale market prices with system costs.

Efficiency of capacity remuneration mechanisms

While there is still a debate about whether capacity remuneration mechanisms are even required (Keppler, 2017), the discussion and the sequential implementation of different mechanisms often already creates a fait accompli. While different problems require different solutions, which may partly explain the vast number of customized solutions (Doorman et al., 2016), it is largely unclear how these numerous mechanisms are to be evaluated in terms of their economic efficiency. As the primary focus is often on the effectiveness of the individual mechanisms and their contribution to generation adequacy, the efficiency tends to be neglected (e.g., Bhagwat et al., 2017a). In some studies, efficiency is addressed, but an overarching comparison is hampered by the fact that no uniform criteria are applied between the studies or comparable assumptions are made (cf. Hach et al., 2016; Traber, 2017). A further complicating factor is that in practice many problems, such as incorrect parameterization or market power of individual participants can occur (Bhagwat et al., 2016b), which further complicate the transfer of theoretical results to practical applications. Therefore, it still is necessary to investigate whether some mechanisms are more cost-efficient and which factors of real-world markets could possibly influence this outcome.

Impact of investment strategies and degree of risk-aversion

The characteristics of investors such as their risk profile and investment strategy is one aspect that plays a significant role for the development of the electricity market, however, is often neglected in modeling and rarely verified by studies or experiments. Nonetheless, the explicit consideration of risk is of immense importance. As shown by Ehrenmann and Smeers (2011), a deterministic analysis might overlook changes in the future capacity structure induced by the various risks to which investors are exposed. Thus, an electricity model that provides agents with different investment strategies, for example, based on concepts such as the conditional value at risk (CVaR), can yield intriguing new insights (e.g., Abani et al., 2018).

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