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Risk Management for Renewable Energy Generation

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How to Deal with the Uncertainty of Wind and Solar Power

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Zusammenfassung

Die Verfügbarkeit von Wind- und Solarenergie ist inhärent unsicher. Während sich die Forschung bislang auf ihre lang- und kurzfristige Unsicherheit konzentriert hat, erhielt der mittelfristige Zeitraum über das kommende Jahr weniger Aufmerksamkeit. Dabei ist er hochrelevant für Investoren, Banken und Versicherungen, sowie Systemplaner. Aus diesem Grund umfasst diese Dissertation drei Aufsätze über den Umgang mit mittelfristiger Unsicherheit in der erneuerbaren Stromerzeugung: in einem virtuellen Kraftwerk, mit Windstromfutures und bei der Nutzung von Investitions- und Einsatzmodellen zur Systemplanung.

Aufsatz I: Viele Eigentümer von Photovoltaik- und Windkraftanlagen nutzen virtuelle Kraftwerke um Zugang zum Strommarkt zu erhalten. Ihre Stromerzeugung ist inhärent unsicher und ihr Umsatz damit riskant. Wir untersuchen in welchem Maß eine Bündelung verschiedener Technologien und Regionen im Portfolio eines virtuellen Kraftwerks das Risiko mindern kann. Zu diesem Zweck entwickeln wir stochastische Modelle für die Faktoren, die das Preis- und Volumenrisiko der Anlagen treiben und setzen ein Modell zur risikooptimierten Portfoliobildung darauf auf. Am Beispiel des deutschen Marktes zeigen wir, dass unsere optimalen Portfolios ein eindeutig besseres Risikoertragsprofil haben als das Marktportfeuille. Diese Erkenntnis gilt für den Fall ohne Subventionen, aber auch für den Fall von Einspeisevergütungen.

Aufsatz II: Windenergie ist unsicher, was sich auf die Gewinne von Windstrom- wie auch von konventionellen Erzeugern auswirkt. Aktuell haben beide Gruppen nur begrenzte Möglichkeiten ihr resultierendes Volumenrisiko abzutreten. Die European Energy Exchange (EEX) führte daher in 2016 börsengehandelte Windstromfutures ein um diese Marktunvollkommenheit zu adressieren. Wir schlagen ein stilisiertes Gleichgewichtsmodell mit zwei repräsentativen Agenten vor und analysieren die erwarteten Preise von Windstromfutures, sowie den Mechanismus hinter ihren Risikoprämien. Wir kalibrieren und simulieren stochastische Modelle für Windstromerzeugung, Strompreise und -nachfrage, sowie weitere relevante Quellen von Unsicherheit. Die damit durchgeführte Fallstudie für den deutschen Markt analysiert Preise, Hedgingeffektivität, sowie Risikoprämien. Unsere Ergebnisse deuten darauf hin, dass Windstromerzeuger bereit sind eine Versicherungsprämie an konventionelle Erzeuger zu zahlen um ihre Risiken zu reduzieren.

Aufsatz III: Der Technologiemix im erneuerbaren Stromsystem kann durch Investitions- und Einsatzmodelle optimiert werden, die Kosten minimieren. Die Ergebnisse dieser Modelle werden stark beeinflusst von ihrer Abbildung der Residuallast, also der Differenz aus Stromverbrauch und erneuerbarer Erzeugung. Aktuelle Modelle fokussieren sich meist entweder auf eine hohe zeitliche Auflösung oder auf eine stochastische Modellierung. Bisherige Forschung zeigt, dass beide Stoßrichtungen die Qualität der Modellergebnisse substanziell verbessern, aber ihre Kombination die erforderliche Rechenleistung stark erhöht. Daher entwickle ich ein sparsames Investitions- und Einsatzmodell, das in der Lage ist zeitlich hochaufgelöste, stochastisch simulierte Eingangsdaten zu verarbeiten. Eine Anwendung des Modells auf das deutsche Stromsystem zeigt den Wert der stochastischen Modellierung. Dasselbe Modell mit deterministischer Residuallast unterschätzt sowohl die erforderliche Windkraft- und Photovoltaik-, als auch die notwendige Speicherkapazität deutlich. Folgerichtig unterschätzt es auch die Systemkosten.

Abstract

The availability of wind and solar energy is inherently uncertain. While much research has focused on dealing with its long- and short-term uncertainty, the medium-term, or the time period over the coming year, has received less attention. Yet it is highly relevant to renewable investors, funding and insurance providers as well as system planners. Hence, this dissertation presents three essays on how to deal with medium-term uncertainty in variable renewable energy generation: in a virtual power plant, with wind power futures and using investment and dispatch models for system planning.

Essay I: Many photovoltaic and wind generation capacity owners gain access to power markets by signing up with virtual power plants. Power generation from these renewable sources of electricity is inherently uncertain and, consequently, revenue is random, which induces a risk for the owner. In this study, we investigate to what extent pooling different technologies and locations in the portfolio of a virtual power plant can reduce aggregate risk. To this end, we develop stochastic models for factors driving the assets' underlying market and volume risks on which we base a model for risk-optimized pooling. Using the German market as an example, we demonstrate that optimal portfolios have a clearly better risk/return profile than the market portfolio. This finding holds in the case without subsidies as well as the case with feed-in tariffs.

Essay II: Generation from wind power plants is uncertain and affects profits of wind power generators and conventional generators alike. Currently, generators have limited options for transferring the resulting wind-related volume risks. The European Energy Exchange (EEX) recently introduced exchange-traded wind power futures to address this market imperfection. We propose a stylized equilibrium pricing model featuring two representative agents and analyze equilibrium prices as well as the mechanics behind risk premia for wind power futures. We calibrate and simulate stochastic models for wind power generation, power prices, electricity demand, as well as other relevant sources of uncertainty and use the resulting scenarios to conduct a case study for the German market, analyzing prices, hedging effectiveness, and risk premia. Our main result suggests that wind generators are willing to pay an insurance premium to conventional generators to reduce their risks.

Essay III: The technology mix in a renewables-based power system can be optimized by investment and dispatch models minimizing cost. These models' outcomes are strongly driven by their representation of residual load, which is the difference between power demand and renewable generation. Models usually either focus on a high temporal resolution or on a stochastic model. Available research suggests that both of these aspects make the model output substantially more accurate (e.g., Haller et al., 2012; Haydt et al., 2011), but their combination strongly increases computational requirements. Hence, I develop a parsimonious investment and dispatch model that allows to be based on residual load with high temporal resolution *and* a stochastic simulation. An application of the model to the German power system demonstrates the value of stochastic modeling. The same model with deterministic residual load underestimates the required wind and solar power, as well as storage capacities. Consequentially, it also underestimates the overall system costs.

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Chapter 1

Introduction

Our current level of greenhouse gas emissions is causing anthropogenic climate change. The resulting warmer temperatures are expected to yield negative consequences for human civilization as we know it. With the Paris Agreement of December 12, 2015, 195 nations have agreed to hold the "increase in the global average temperature to well below $2°$ C above pre-industrial levels and to pursue efforts to limit the temperature increase to $1.5°$ C above pre-industrial levels, recognizing that this would significantly reduce the risks and impacts of climate change".

The signing parties also agree that net anthropogenic emissions need to be reduced to *zero* in the second half of the 21st century to reach the $2°$ C objective (United Nations Framework Convention on Climate Change, 2015). In any case, a reduction of this magnitude is a mammoth task for the next couple of generations.

Today the large majority of CO_2 and other climate-damaging emissions are created by energy conversion processes with which humans generate or consume energy. Hence, the task at hand is to transition to energy carriers, which can be generated and consumed without emitting greenhouse gases. Popular candidates for emission-free energy carriers are power, hydrogen and biomass, among which power has gained a pole position as it can be generated and consumed much more efficiently than hydrogen and be used on a larger scale than biomass.

Hence, mainly two complementary lines of attack are pursued at the moment to advance the global energy transition:

1. *Consume more power instead of other energy carriers:* Heat generation and transportation are our two main applications of currently non-electrified energy consumption.

2. *Generate more emission-free power:* This requires a shift of power generation to emission-free technologies such as PV (photovoltaic), wind, hydro, nuclear, geothermal or biogas-fired power generation. This line of attack is the general focus of my dissertation.

Among emission-free power generation technologies, PV and wind power are clearly the winners of the technology race. The main reasons are their large resource potential, fast build-out pace and low cost. For these reasons, PV and wind power attracted 95% of renewable energy investments in 2015; a sum of 270 billion USD (UN Environment Programme et al., 2016). But PV and wind power generation is *variable*, which means it has three unique characteristics: intermittency, uncertainty and decentrality (Hirth et al., 2015).

1. *Intermittency* is the uninfluencable weather-dependent variation in PV and wind power generation over time. Output cannot be adjusted to match demand in the same way as it is possible with conventional power plants. Hence, other dispatchable generation capacities are required to satisfy demand during times of low variable generation.

2. The *uncertainty* of PV and wind power at a specific point in time results in deviations between forecasted and actual generation volume. The deviations are substantially greater than for conventional power plants and create challenges in a large number of areas discussed later in this section.

3. The *decentral* nature of PV and wind power, away from today's geographic consumption centers, requires the expansion of grids to transport generated power to its place of consumption. This definition of decentrality has a wider scope than its more narrow meaning of 'power plants being installed on consumer's premises'.

Conventional generation technologies, such as gas- or coal-fired generation, do not show these three characteristics. Consequently, PV and wind power cannot replace them in a 'plug-and-play' fashion. A transition of the entire power system, including all of its components, is necessary to cope with intermittency, uncertainty and decentrality. Any lack of their detailed understanding is likely to disturb the energy transition process and make it either more costly or more timely. It might also derail the transition process altogether.

Hence, research that expands the detailed understanding of the three characteristics is valuable and this dissertation's objective is to contribute to it. Its focus is thereby on the *uncertainty characteristic*, which is arguably the least obvious of the three. After all, intermittency is the cornerstone characteristic for PV and wind power. In fact the term 'intermittent' is often used synonymously to 'variable' renewables. Decentrality is taken into consideration during every investment decision for a variable generation site or a network expansion. Uncertainty, on the contrary, can be most easily overlooked.

This is true in particular for *medium-term uncertainty*; defined here as uncertainty about generation volumes in the *coming months to years*. As I demonstrate in the following section it is far less researched than short-term uncertainty over the next minutes to weeks or long-term uncertainty over greater than 10 years, which is the typical investment horizon for PV and wind power plants. Nevertheless, medium-term uncertainty is substantial. The yearly German-wide utilization of wind power plants for instance has varied between 14% and 22% from 2011 to 2014 (see Section 2.3 for details).

1.1 One overarching research question

The three essays in my dissertation can be subsumed under one overarching research question:

How to deal with the medium-term uncertainty of wind and solar power?

To illustrate the question's relevance, I ask 'Who needs to deal with medium-term uncertainty?' and differentiate between a micro- and a macroeconomic perspective.

On the one hand, the central actors with a *microeconomic* perspective are PV and wind power investors. They make a CAPEX-heavy and typically highly leveraged investment decision. Medium-term uncertainty in their generation volumes naturally leads to volatility in their revenues over the course of the power plant's lifetime. Moreover, as subsidy mechanisms change, power price risks also become more relevant to renewable energy investors, which additionally increases volatility. The resulting revenue volatility in turn requires less leveraging and/or higher liquidity, which both raise the overall costs of variable renewable energy sources.

Several other actors are affected by medium-term uncertainty in variable generation as well. Conventional generators are exposed to volume risks, as their own generation volume and prices are negatively correlated to renewable generation volume. Hence, a good wind year is likely a bad year for conventional generators.

Retailers, offering 'green power' to their customers, usually buy certificates of origin to guarantee that their customer's demand has actually been generated from 'green sources'. Prices for these certificates are likely to vary inversely to uncertain supply. Service providers, such as direct marketeers, typically have volume-dependent service fees and a high share of fixed costs. Hence, volatility in generation volume is a big risk for their business model. Moreover, banks, financing renewable energy generation investments, are likely to incorporate a quantification of medium-term risks in their credit ratings. Insurance companies, offering policies to reduce volume risk, also need that quantification.

On the other hand, the *macroeconomic* perspective is assumed by a social planner, who maximizes the welfare the power system generates. In order to do that, she adjusts all capacities in the system to ensure security of supply, sustainability and efficiency. Medium-term uncertainty about renewable generation volumes combines with uncertainty of demand patterns. Hence, it is not certain for which conditions the system should be laid out. A lack in understanding of medium-term uncertainty, for instance an overestimation of PV or wind power's availability, can lead to reduced welfare. Either the system is potentially insecure, not as sustainable as planned, or inefficient. Planning procedures obviously need to prevent this by incorporating all possible realizations of uncertain variable generation.

Although medium-term uncertainty is highly relevant, it is the least researched time frame of uncertainty in renewable generation volumes. Instead, the focus has so far been on the long- and the short-term. In comparison though, medium-term uncertainty is the one that will largely remain inherent to PV and wind power generation, while long- and short-term uncertainty are more easily dealt with. This results from two aspects.

On the one hand, the inherent randomness of variable generation volumes is very large for short time periods; such as the next 15 min or the next hour. As the time period becomes longer, uncertainty obviously decreases. Hence, wind and solar power generation over the long-term, or the typical investment horizon, is not as volatile, because yearly meteorological variations even out. In this respect, variable generation differs structurally from typical behavior of stock prices or the like.

On the other hand, variable generation is, like the weather, strongly path-dependent. Consequently, short-term forecast models can explain a substantially larger share of inherent randomness than long-term models.

Variable generation over the medium-term time frame is 'stuck in the middle'. While it is still highly random, forecast models largely fail to accurately predict it. Hence, challenges from medium-term uncertainty will have to be met by dealing with the uncertainty itself and this dissertation examines three ways to do that. To my knowledge, there is currently no research that puts medium-term uncertainty at the core of its questions. Hence, I consider it a novel field of research and hope this dissertation contributes to its development.

Research on long-term uncertainty has mostly addressed the needs of renewable energy investors that needed to understand the distribution of generation volumes over their investment horizon. Forecasts are site-specific and the availability of site-specific meteorological data greatly improves the forecast quality. Thereby, long-term forecasts have reached average percentage errors of 3% (Weekes et al., 2015).

Research on short-term uncertainty, first, aims to improve the variable generation forecasts made one week to several minutes ahead of realization. Second, it develops solutions for short-term balancing of these forecast errors. Both approaches are required to ensure system stability efficiently and keep it that way when PV and wind power is increasingly built out. System stability has originally been the sole responsibility of the system operator. In some markets, such as in Germany, the responsibility for balancing renewables has increasingly moved to the individual plant operators. With a subsidy scheme such as direct marketing, the renewable power generator itself promises a feed-in schedule one day ahead of delivery and has to balance out potential deviations on the intraday market or pay respective penalties for them. Ongoing research efforts and the increased interest by investors themselves in better short-term forecasts for uncertain generation have substantially improved their quality (Foley et al., 2012).

I define a simple two-dimensional framework to sort the various incarnations of my research question. Based on our previous question 'Who needs to deal with uncertainty?', I call the first dimension the *perspective* and differentiate, as before, between the micro- and the macroeconomic perspective. Furthermore I choose the renewables investor as an

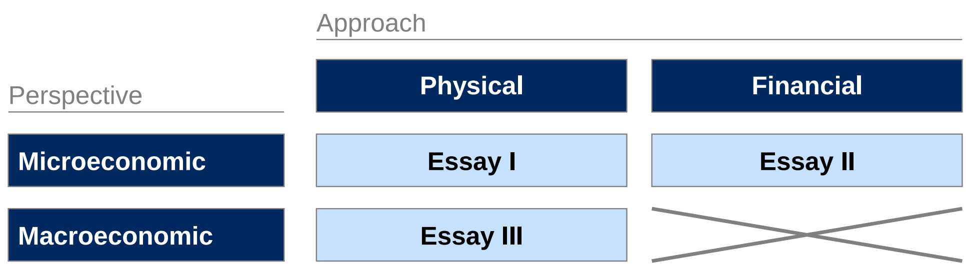


Figure 1.1: Location of the three essays in this dissertation along two proposed dimensions of dealing with wind and solar power's medium-term uncertainty: the perspective and the approach.

example for the micro- and the system planner as an example for the macroeconomic perspective.

The second dimension classifies research by the *approach* applied to deal with uncertainty. As medium-term uncertainty will naturally remain inherent to PV and wind power generation respectively, its risks can only be reduced through the combination with a balancing mechanism. The investor with the microeconomic perspective can choose a *physical* or a *financial* balancing mechanism. The system planner on the other hand can only use a *physical* mechanism as he has to ensure security of supply at all times.

Figure 1 combines perspectives and approaches and locates the three essays in this dissertation accordingly. Essays I and II assume the microeconomic perspective and respectively treat a physical and a financial approach. Essay III assumes the perspective of a system planner and analyzes her possibilities to reduce risk with different physical system components. The three essays' research questions are as follows.

- *Essay I:* To what extent can pooling of different technologies and different locations in the portfolio of a virtual power plant reduce its aggregate risk?

- *Essay II:* How can wind power futures be priced and what are the mechanics behind their potential risk premia?

- *Essay III:* What is the effect of stochastic and dynamic residual load modeling on the optimal technology mix in a renewables-based power system?

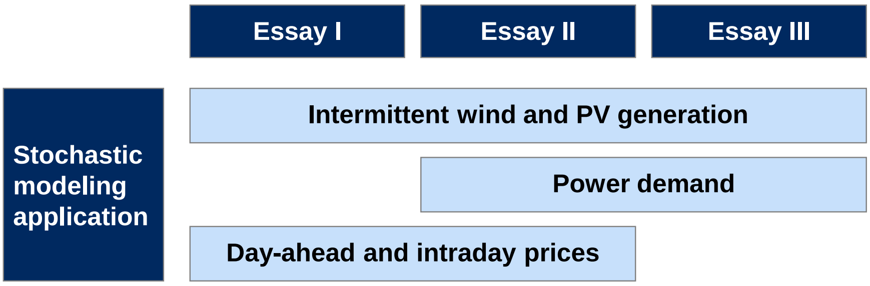


Figure 1.2: Application of stochastic models throughout the three essays in this dissertation.

All three questions are novel and cover different aspects of how to deal with the medium-term uncertainty of PV and wind power generation. Hence, all essays aim to contribute to this dissertation's overarching research question.

1.2 One methodological foundation

Next to a shared overarching question there is also a methodological thread that links the three essays in this thesis together. Answers to their research questions require a stochastic *modeling of medium-term uncertainty*. It does not only need to provide reasonable forecasts for the risk factors, but also needs to be able to mimic their distributional properties. The chosen models, fulfilling this requirement, are developed and explained in Essay I. They are all non-parametric, consider yearly and daily seasonality, have hourly resolution and simulate a set of scenarios for each risk factor.

In order to give an overview of the stochastic models developed for this research, Figure 1.2 shows which ones are used in which of the three essays. The stochastic simulation of PV and wind power generation is obviously a common building block in all of them. It is complemented with models for short-term PV and wind power forecasts and resulting forecast errors. But to fully incorporate the existing medium-term risks, other factors need to be modeled as well. A full simulation of power demand is necessary for Essays II and III. The simulation of power prices, inter alia based on a simulation of temperatures and natural gas prices, is used in Essays I and II that assume the investor perspective.

The diverse applications of the developed stochastic models demonstrate their relevance in a renewables-based power system, for risk management in particular and for decision making in general. Hence, they are a contribution in their own right and can be applied, as documented here, to other decisions and research questions.

Chapter 2

Risk-Optimized Pooling of Variable Renewable Energy Sources

written in collaboration with Prof. Dr. David Wozabal

Many photovoltaic and wind generation capacity owners gain access to power markets by signing up with virtual power plants. Power generation from these renewable sources of electricity is inherently uncertain and, consequently, revenue is random, which induces a risk for the owner. In this study, we investigate to what extent pooling different technologies and locations in the portfolio of a virtual power plant can reduce aggregate risk. To this end, we develop stochastic models for factors driving the assets' underlying market and volume risks on which we base a model for risk-optimized pooling. Using the German market as an example, we demonstrate that optimal portfolios have a clearly better risk/return profile than the market portfolio. This finding holds in the case without subsidies as well as the case with feed-in tariffs.

2.1 Introduction

Driven by declining capacity prices and generous subsidy schemes, the number of photovoltaic (PV) and wind power plants around the world has been growing rapidly over the last 10 years. This trend is likely to continue due to the urgent need to decarbonize the world's energy generation and thereby reduce greenhouse gas emissions and minimize global warming. However, PV and wind power plants have an important characteristic: their generation is *uncertain*, that is, the generation cannot be controlled and depends on fluctuating weather conditions, which makes it difficult to accurately forecast output.

To facilitate an efficient power system, PV and wind power plants need to be integrated into the power market to send and receive useful coordination signals. Due to the distributed nature of PV and wind power, their integration is complicated by the prohibitively high entrance barriers of power markets, set up for professional traders requiring 24x7 operations along with forecasting and real-time balancing, thus incurring significant transaction costs.

We consider the problem of a service provider acting as an intermediary between distributed energy sources and the wholesale power market. We call such entities *virtual power plants (VPPs)* (Pudjianto et al., 2007). The main share of power market volume in future renewables-based energy systems is likely to come from PV and wind power plants (Fraunhofer IWES, 2015a). Since owners of these plants usually do not have their own trading infrastructure, VPPs are a means to facilitate their market integration.

Sharing transaction costs associated with market entry is currently seen as the main reason for pooling distributed energy sources in a VPP (economies of scale). In this paper, we discuss the potential risk reduction for the owners of variable renewable energy sources (economies of scope), which is another, albeit less obvious, advantage of pooling. We investigate how much a VPP can improve the risk/return profile, thus creating additional value with its service by contracting a carefully chosen mix of renewable capacities. For this paper, we limit our analysis to variable renewable energy sources from PV and wind power, which comprise the majority of renewable capacity installations. Hereafter, we refer to these capacities as *renewable energy sources* or as *renewables*.

There is a growing body of literature on VPPs. Ilic et al. (2007) indicate the importance of VPPs when transforming from a central to a distributed power system by enabling near-optimal dispatch and investment decisions, otherwise impossible. Pudjianto et al. (2007) describe VPPs as the primary vehicle to deliver cost-efficient integration of renewable energy sources and differentiate between a technical and a commercial VPP (TVPP and CVPP, respectively). A TVPP manages a local network zone or control area and ensures network stability in the face of variable generation. A CVPP develops flexibility options, combines them with renewable sources, and integrates them into the existing power markets. In the present paper, we adopt the perspective of a CVPP.

The literature on VPP decision making under uncertainty can be grouped in three streams. The first stream focuses on investment sizing for distributed energy sources, minimizing total system costs. Many studies concentrate on local pools, which combine different technologies. Ekren and Ekren (2009), for instance, optimize a setup with PV and wind generation combined with battery storage.

The second stream of studies aims to minimize the short-term generation cost by optimizing the dispatch decision for existing pools of distributed energy sources. Usually studies examine island systems without access to power markets. Therefore, the need to fulfill power demand in the respective time period constrains the dispatch decision (Handschin et al., 2006; Molderink et al., 2010).

A third literature stream has developed around optimizing the short-term dispatch decision to maximize the revenue from trading on power markets; we use this setup in our analysis. These papers can be classified according to the different markets they include in their analysis. Pandžić et al. (2013) included forward markets and day-ahead trading in their model and combine renewable and conventional generation with a storage system where uncertainty is included in the form of renewable generation and market prices.

Vasirani et al. (2013) modeled a continuous dispatch re-optimization of a virtual power plant consisting of wind power plants and electric vehicles. They included day-ahead and intraday markets and a payment scheme for the electric vehicle owners.

All abovementioned papers solve the problem of the VPP in order to maximize expected profit, that is, assuming a risk-neutral decision maker. We contribute to the extant literature by investigating a risk-averse VPP. In particular, we frame the decision of the VPP as a medium-term portfolio selection problem, that is, the decision on how much of which type of generation resource to include in the portfolio. To this end, we apply a mean risk approach using Conditional Value-at-Risk (CVaR) as a risk measure.

We contribute to the literature in three ways. First, we expand the literature on the market value of PV and wind power by incorporating their risk patterns and interdependencies into the valuation. Although risk management is one of the central topics in energy finance (Eydeland and Wolyniec, 2003; Pilipović, 2007) and the importance of portfolio optimization in commodity markets is well established in the literature (D'Ecclesia, 2008; Elton and Gruber, 1997), research on the risk-optimal combination of variable renewable energy sources in a virtual power plant is limited. The connection between ideas of portfolio optimization and risk management on the one hand and the problem of marketing renewables on the other is the primary conceptual contribution of this paper.

Second, we suggest several methodologies for improving VPP operations and decision making in the form of non-parametric stochastic models for renewable generation and power prices, that is, the factors driving market and volume risk. These models offer accurate descriptions of the random dynamics of the involved risk factors and have further applications in energy finance beyond this paper.

Third, we enhance the conceptual understanding of the VPP's intermediary role in the power system by describing an additional set of benefits it offers not only to owners but also the system as a whole. In particular, we demonstrate that a VPP can create substantial value by diversifying risk for the owners of individual renewable generation capacity through efficient portfolios, dominating the German market portfolio in the sense of second-order stochastic dominance (SSD). This implies that the risk-optimized portfolios are better than the market portfolios independent of the risk preferences of the decision maker. The relevance of this aspect will increase as the industry matures and consolidates while subsidy schemes are reduced and renewables start to compete with other generation sources in the power market. Hence, diversification in a VPP offers an opportunity to substantially increase the attractiveness of renewable power generation for owners and operators; offsetting some of the inherent disadvantages of uncertainty.

We provide two extensions of our model to demonstrate its wide applicability in different setups. First, we assume the perspective of a VPP operator guaranteeing prices to the owners of pooled renewables, much like feed-in schemes guarantee fixed tariffs. In this case, the VPP operator is exposed to the full market risk and, correspondingly, the effect of risk diversification is much higher than for our base case, as the VPP carries a higher risk compared with the expected return. Second, we set up a model for renewable asset owners without any access to power markets, who receive feed-in tariffs for their generation, that is, a model without any market risk. Risk-optimized pooling also offers advantages in this setting, allowing us to conclude that value can be captured independent of compensation setup.

The results for the different model variants additionally inform the debate on renewable subsidy policies and resulting risk distribution. In particular, our main model quantifies the distribution of price and volume risks between regulator and investor in the case of a subsidy scheme with market price premiums. Our model variant II quantifies the risk distribution in a situation with feed-in tariffs. Our results show that the investor's overall risk is substantial in both subsidy schemes.

In our models, we use the German market as an example because of its high share of renewable generation, whose growth, in the past, was mainly driven by high feed-in tariffs. In this sense, the German situation can be seen as a model for expected future situations in many countries. Also in most other respects the German electricity market resembles that of many other European countries as well as parts of the US – at least when it comes to market rules relevant for medium-term planning, which is the focus of our paper. Additionally, risk and correlation structures driven by weather patterns are similar in most markets[1]. Hence, we are confident that the main findings of our paper are applicable to most countries with a large share of variable generation.

Furthermore, the German market is an appropriate example because the regulator encourages renewable capacity owners to sell their generation directly in the wholesale electricity market; introducing a demand for VPP services. Since 2012, the total VPP capacity in Germany has increased considerably: 39.9 GW (52%) of variable renewable capacity was marketed by VPPs by the end of 2014. This development was driven by a regulatory push to support direct marketing (DM). DM describes the process of selling generation subsidized by the *Renewable Energies Act* directly on the wholesale power market. By doing so, asset owners receive a premium over and above the market revenues. Since January 1, 2016, all newly installed assets with a capacity greater than a 100 kW capacity must obligatorily participate in DM. Integrating renewables into the wholesale power market aligns the producers' incentives with market signals, which makes it profitable for them to invest in efficient operation (e.g., accurate weather forecasts and good locations).

Overall this regulatory push has established a strong position of VPPs. By the end of 2014, 88% of German on-shore wind, 90% of off-shore wind and 17% of PV capacity were directly marketed (Bundesnetzagentur, 2015). Several new market participants had sprung up that manage around 2.5–3.5 GW of renewable generation each. The largest provider, Statkraft, sold generation from around 9 GW of capacity while the largest 10

[1] In particular, the correlation of wind power and PV generation as well as the correlation of power prices with renewable generation are likely to carry over to most other markets.

VPPs sold around 75% of the variable renewables' market volume. Hence, the introduction of DM has brought forward significant pooling of renewable assets into larger VPP portfolios (Köpke, 2015).

The rest of the paper is structured as follows. In Section 2.2, we discuss our assumptions, setup and the optimization model. Section 2.3, describes the stochastic models used to simulate our underlying risk factors. The results for the German market are discussed in Section 2.4. We provide conclusion and outlook on further research questions in Section 2.5.

2.2 Model and assumptions

In this section, we first discuss the setup and assumptions of our study in Section 2.2.1. Then, we describe the two-stage stochastic optimization model used to calculate risk-optimized VPP portfolios in Section 2.2.2.

2.2.1 Setup and assumptions

In our main model, we adopt the perspective of a VPP deciding on its portfolio of renewables while optimizing the risk/return profile of the joint portfolio revenues. In general, a VPP receives revenues from selling power, generated by its clients, in the spot market for electricity. The VPP's risk is driven by portfolios' uncertain generation volume (*volume risk*) and uncertain future spot market prices (*market risk*).

The effect that electricity price fluctuations have on VPP revenue depends on the subsidy scheme. We analyze two cases: first, the case without any subsidies wherin the portfolio is subject to full market and volume risk (main model) and second, the case wherin the VPP gets fixed feed-in tariffs, which remove the market risk entirely (model variant II). In current regulatory practice, several combinations of these models exist in which asset owners share a part of the market risk.

We assume that VPPs act risk-averse, that is, care about risks and not only about the expected rewards of their operation. Since energy trading companies routinely use the theoretical and institutional foundations developed for risk management in banks and report the riskiness of their positions in their financial statements, this appears to be a reasonably innocuous assumption.

Considering that renewable generation investments typically rely on a high level of debt financing, requiring at least yearly servicing, active management of revenue risk is essential (Fraunhofer IWES, 2015b). Clearly, combining different kinds of variable renewable energy sources potentially reduces the VPP's revenue risk and in turn the risk for the participating capacity owners. This study aims to quantify this effect by considering the problem of optimally combining renewables in a VPP, that is, a portfolio of generation assets. This problem takes a form that very much resembles classical portfolio theory, where the aim is to (risk-)optimally combine different financial assets. As in portfolio theory, the non-trivial correlation structure between different assets allows for improvements of the the risk/return profile. An example of this is the negative correlation between cumulative yearly output of PV and wind capacities, which seems to exist in Germany.

We assume the VPP sells power in the EPEX power exchange, which comprises two market segments: *day-ahead* and *intraday*. The day-ahead market works in the form of an auction resulting in a uniform clearing price for power delivery in each hour of the following day. Trading on the intraday market for 15-min slots of the respective day starts after the auction results are published and takes place continuously until 30 min before fulfillment.

The VPP in our model sells the forecast amount of renewable generation from its portfolio on the day-ahead market and balances forecast errors on the intraday market. The reason for trading on the day-ahead market instead of selling the entire generation on the intraday market is illustrated in Figure 2.1, indicating that the liquidity of EPEX

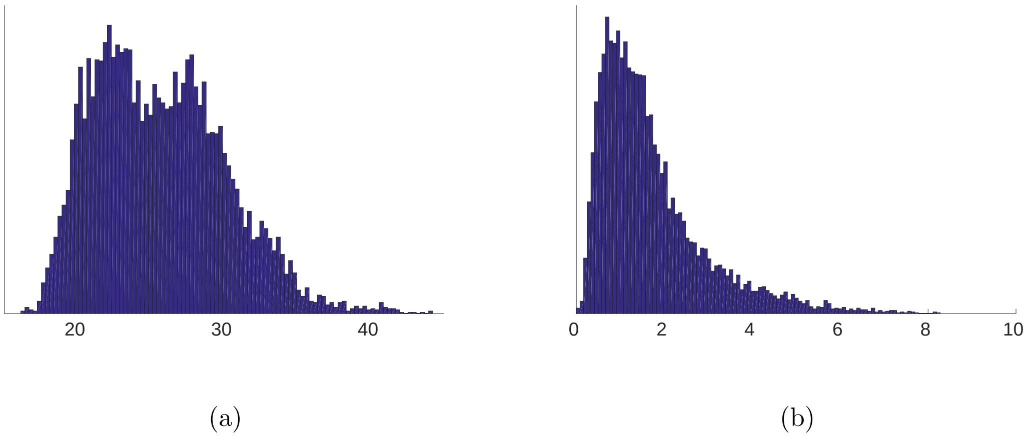


Figure 2.1: Distribution of trading volumes in GW per fulfillment hour on the German-Austrian EPEX day-ahead [panel (a)] and on the EPEX intraday market [panel (b)] in 2014.

intraday market is not sufficient to absorb the entire generation from a typical VPP. As several German VPPs manage more than 3 GW, their full load would have exceeded the intraday market volume in more than 75% of all hours in 2014. Although the intraday market has gained in importance, on average it still accounts for only 8% of the day-ahead market's volume.

Further, we assume that forecasting errors, which occur during the last 30 min before fulfillment (after the intraday market closes), are sufficiently small to be disregarded and that the intraday market is, at all times, liquid enough to absorb the VPP forecasting errors. Hence, we do not include additional balancing penalties resulting from very short-term forecasting errors. This is in line with increasingly short lead times in the intraday market and with progress in short-term weather forecasting. Furthermore, the VPP in our model does not participate in the futures market because the *flat* profile of futures delivery requires constant volume delivery over longer periods of time, which is incompatible with the fluctuating pattern of PV and wind generation.

Note that the asset owners join the VPP solely to optimize their *revenues*. They cannot expect any diversification benefits from pooling their costs, because costs are largely independent for different assets. This is certainly the case for capital expenditures, comprising the majority share of total renewable costs: they are sunk at the time the asset owner is signing up with a VPP. Further, we assume the different assets' operational expenditures to be largely independent. Consequently, we do not consider any costs in our approach, which is in line with the situation in practice. Asset owners carry their own costs and try to minimize them to the best of their abilities. They use the VPP solely to optimize their revenues. Moreover, since we are interested in the benefits of diversification and not in the obvious positive effects a VPP can generate from exploiting economies of scale, first, we are careful not to model any fixed transaction costs to avoid effects of cost degression with increasing size, and second, restrict the portfolio to a fixed size.

Lastly, in this paper, we focus on the value that can be generated by pooling, but we do not investigate the question how the revenues should be distributed optimally between the asset owners and the VPP operator. We assume that VPP operators and asset owners will find a set of transfer prices allowing them to capture additional value from risk diversification and benefiting all parties.

2.2.2 Portfolio optimization models

In this section, we discuss the optimization model used to decide on the relative weights $w_1, \ldots, w_M$ of the M different assets represented by different renewable technologies in different locations. We use the Conditional Value-at-Risk (CVaR) to model the risk preferences of the aggregator. The CVaR was proposed by Artzner et al. (1999) and enjoys favorable theoretical properties as well as a close connection to the Value-at-Risk which is an industry standard in the banking and insurance industry and to which it is clearly preferable (Mulvey and Erkan, 2006; Szegö, 2002). Furthermore, for the reasons mentioned above, using the CVaR to express risk preferences is fairly standard in energy trading and investment applications (Conejo et al., 2016).

We assume that the VPP does not contract the renewable energy sources for their whole life span. Instead, the individual plants sign up for a VPP for a limited amount of time so as to have the possibility to switch VPPs when market conditions change. In our study, the period under consideration is one year. Due to the yearly seasonality in PV and wind in-feed and the transaction costs related to changing the VPP, this seems to be a reasonable minimum time for a commitment. As we learned from our discussions with market participants, this corresponds to the typical contract durations offered by VPPs in Germany. The VPP takes a portfolio decision for the year 2015 based on scenarios for the stochastic inputs discussed in Section 2.3, which are based on data from the years 2011–14. We select a portfolio with an expected output of 1 MWh per year and impose the following budget constraint on our portfolio weights

$$\sum_{m=1}^{M} w_m = 1, \tag{2.1}$$

where w_m is the expected generation of the portfolio asset m. To translate the weights into asset capacities, we use capacity factors c_m, which indicate how much installed capacity of asset m is required to produce an average of 1 MWh output per year. We estimate $c_1, \ldots, c_M$ based on our simulations for our out-of-sample year 2015 as is discussed below. To avoid integer decisions and keep the model tractable, the decisions are represented by continuous asset weights. This simplifying assumption is standard in portfolio theory and can be justified by the size of the VPPs, which manage a large number of renewable energy sources.

We model the portfolio selection problem as a two-stage stochastic optimization. The here-and-now decisions are the portfolio weights, while the second stage consists of one year of trading on the day-ahead as well as the intraday market. All decisions taken in the second stage are wait-and-see decisions, that is, allowed to depend on the realization of the random risk factors in our models. The fact that we trade exactly the forecast volumes on the day-ahead market and clear imbalances at the intraday market avoids problems with anticipative bidding strategies that result in arbitrage between the two markets.

We represent randomness by a finite number of scenarios S. For the purpose of the model description, we denote the scenarios for the generation forecasts in MWh for one MW of capacity by $\hat{x}_{s1}, \ldots, \hat{x}_{sT}$, $s = 1, \ldots, S$, where $\hat{x}_{st} = (\hat{x}_{st1}, \ldots, \hat{x}_{stM})$ is a vector holding the forecasts for all the M assets in scenario s at time t. Similarly, we define the scenarios for the actual generation in MWh for one MW of capacity by $x_{s1}, \ldots, x_{sT}$, $s = 1, \ldots, S$, while the scenarios for the intraday and day-ahead price scenarios are denoted by $p^I_{s1}, \ldots, p^I_{sT}$ and $p^D_{s1}, \ldots, p^D_{sT}$, $s = 1, \ldots, S$, respectively. We estimate the capacity factors $c_1, \ldots, c_M$ mentioned above as

$$c_m = (ST)^{-1} \sum_{s=1}^{S} \sum_{t=1}^{T} x_{stm}, \tag{2.2}$$

that is, c_m is the average amount of hourly production in MWh from one MW of capacity of type m.

In our main model, we define

$$\pi_{sm} = c_m^{-1} \sum_{t=1}^{T} \hat{x}_{stm} p^D_{st} + (x_{stm} - \hat{x}_{stm}) p^I_{st}, \quad \forall s = 1, \ldots, S \tag{2.3}$$

to be the revenue in scenario s for asset m generating 1 MWh of power with $\pi_s = (\pi_{s1}, \ldots, \pi_{sM})^\top$. Then, putting it all together and using the linear programming formulation of the CVaR proposed in Rockafellar and Uryasev (2000, 2002), we can write our stochastic optimization problem as

$$\begin{aligned} \max \quad & a - \tfrac{1}{\alpha S} \textstyle\sum_{s=1}^{S} z_s \\ \text{s.t.} \quad & S^{-1} \textstyle\sum_{s=1}^{S} \langle \pi_s, w \rangle \geq l \\ & z_s \geq 0,\ z_s \geq a - \langle \pi_s, w \rangle,\ \forall s = 1, \ldots, S \\ & w \geq 0,\ (2.1),\ (2.3) \end{aligned} \tag{2.4}$$

where the decision variable a is the Value-at-Risk (VaR) at level α, z_s is the shortfall below the VaR in scenario s, and $\langle \cdot, \cdot \rangle$ is the inner product in $\mathbb{R}^M$. Note that the lower bound on the expectation in the constraints in (2.4) defines the risk preferences of the investor: the higher l the lower the optimal CVaR and the riskier the portfolio decision.

For our two model variants, only the revenue function π_{sm} needs to be adjusted. In our first variant, the VPP operator's revenue in (2.3) is reduced by a transfer payment to the asset owners based on a set of asset-specific transfer prices

$$p_m^T = S^{-1} \sum_{s=1}^{S} \pi_{sm} - f. \tag{2.5}$$

The p_m^T are calculated such that the expected service fee is f EUR/MWh for every asset. Consequently, the revenues are defined as

$$\pi_{sm}^{Operator} = \pi_{sm} - c_m^{-1} p_m^T \sum_{t=1}^{T} x_{stm}, \quad \forall s = 1, \ldots, S. \tag{2.6}$$

For our second variant, the revenue for the VPP without market access receiving feed-in tariffs p_m^{FiT} for each generated MWh in scenario s for asset m is defined as

$$\pi_{sm}^{FiT} = c_m^{-1} p_m^{FiT} \sum_{t=1}^{T} x_{stm} \quad \forall s = 1, \ldots, S. \tag{2.7}$$

2.2.3 Estimation of marginal asset values

By calculating the marginal benefit of our respective assets in the portfolio, we better understand the price that the VPP would be willing to pay for them; we will call this benefit the *portfolio value* of a specific asset hereafter. Additionally to analyzing its absolute size, we examine how it differs from an asset's expected value. We call this difference either a *premium* or a *discount* of a specific asset at a given level of the VPP's risk aversion. This analysis reveals another dimension of PV and wind asset valuation, which arises because of the asset's risk characteristics and the corresponding value that a risk-averse VPP would assign to it.

Let π be random revenues and

$$\lambda \mathbb{E}(\pi) + \mathrm{CVaR}(\pi) \tag{2.8}$$

be the utility function of the VPP, with the parameter λ as the dual variable of the expectation constraint in (2.4). We determine how much the VPP would be willing to pay for an increase in its position in asset m by determining the marginal utility from an increase in the respective asset's weight w_m transformed into a monetary value. To this end, we calculate the partial derivative $\frac{\partial}{\partial w_m} u(w^*)$ of the utility function at the optimal solution w^* that solves (2.4)[2].

We define the *portfolio value* of asset m as the deterministic monetary value, which the VPP is willing to pay for an extra unit of the respective asset, calculated based on utility function (2.8) and the translation invariance of the CVaR as

$$(1+\lambda)^{-1} \frac{\partial}{\partial w_m} u(w^*). \tag{2.9}$$

Furthermore, we define *market premiums/discounts* for individual assets m as

$$(1+\lambda)^{-1} \frac{\partial}{\partial w_m} u(w^*) - S^{-1} \sum_{s=1}^{S} \pi_{sm}, \tag{2.10}$$

that is, the difference between the portfolio value and the expected revenue of asset m. If the above value is larger than zero, then the VPP would pay a *premium* on top of the asset's expected revenue, whereas a negative value signifies that the VPP would only accept an additional unit of asset m if it were offered at a *discount* from its expected revenue.

2.3 Modeling of stochastic inputs

In this section, we discuss the stochastic modeling of the risk factors that influence the VPP's revenue and are required to build the scenarios used in Section 2.2. We can broadly categorize the risk factors as variables influencing revenue by their impact on power

[2] Note that

$$\frac{\partial}{\partial w_m} u(w^*) = \frac{\partial}{\partial w_m} \left(\lambda \mathbb{E}(\langle w^*, \pi_s \rangle) + \mathrm{CVaR}(\langle w^*, \pi_s \rangle)\right) = \frac{\lambda}{S} \sum_{s=1}^{S} \pi_{sm} + \frac{1}{\alpha S} \sum_{s \in \mathcal{I}} \pi_{sm}$$

given that αS is an integer and $\mathcal{I} = \{s : \langle w^*, \pi_s \rangle \leq a^*\}$ with a^* the Value-at-Risk of the optimal portfolio, which is the optimal value for a in (2.4).

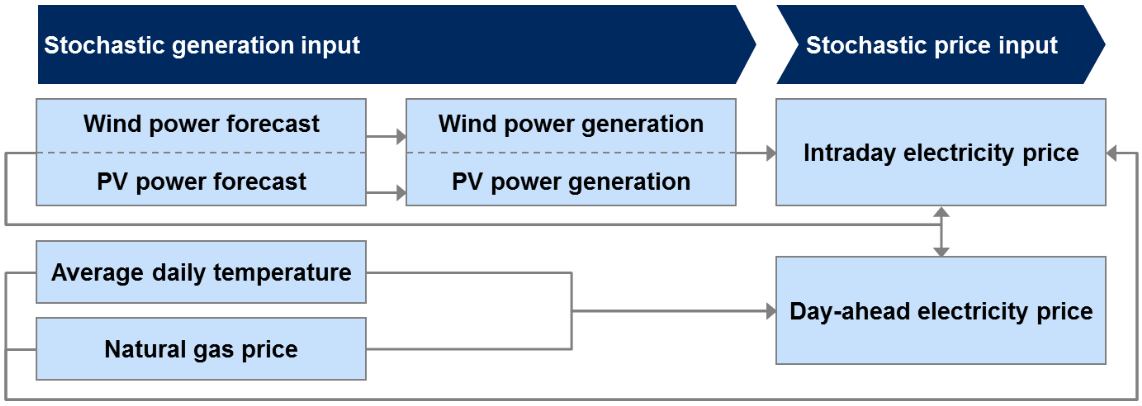


Figure 2.2: Simulated risk factors and their interdependencies.

prices and those impacting the generated power volume. Variables with direct impact on generation volume also may impact power prices.

To be able to quantify the portfolio risk and decide the portfolio composition, we require stochastic models for all the uncertain parameters in our model. An overview of the modeled variables and their connections is provided in Figure 2.2.

1. As a central building block, we describe random generation volumes from the renewable energy sources. We model PV and wind generation separately for each network zone in Germany, capturing geographically varying generation patterns. We model forecast outputs as well as actual outputs[3].

2. As additional input for our electricity price models, we model the average daily temperature, which influences the demand for electricity and captures seasonality within the year.

3. We use the natural gas price as a proxy for prices of primary energy carriers in our electricity price models and use a mean reverting process, with a non-constant mean reversion level, to represent its random evolution.

4. We model random day-ahead as well as intraday prices. The day-ahead price models

[3] The network zones in Germany are Tennet, 50Hertz, Amprion and TransnetBW

are regression models with temperature, gas price, and forecasts for renewable infeed as explanatory variables. The intraday price depends on the same factors as the day-ahead price but additionally takes the day-ahead price and the forecast error in renewable generation into account.

To be able to capture the impact of risk on the portfolio decision, we build models that not only provide reasonable forecasts for the risk factors but also can mimic the distributional properties of the real processes when simulated over longer periods of time. In this respect, our approach differs from the large majority of existing literature, which is either focused on short-term forecasts for operation and trading purposes or on long-term forecasts for investment decisions. We choose a fully non-parametric approach to modeling the stochastic input factors $(X_t)_{t=1}^T$. All the models consist of a trend $(Y_t)_{t=1}^T$ which may depend on other stochastic factors and a random deviation $(\epsilon_t)_{t=1}^T$ from the trend. All models are estimated using four years of data from 2011 to 2014. We denote the in-sample time (in hourly time steps) as $t = 1, \dots, T$.

We choose a unified modeling approach for PV and wind power forecasts, temperatures and gas prices. The trend $(Y_t)_{t=1}^T$ is deterministic, dependent only on time, and estimated using locally constant kernel regression

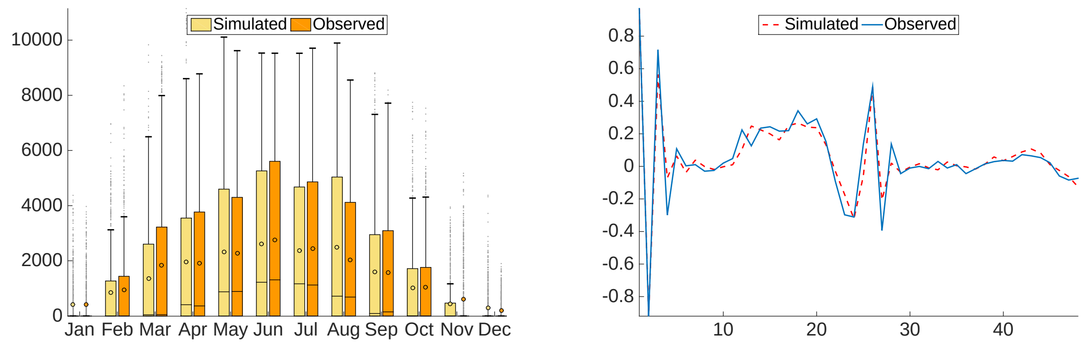
$$Y_{F(t)} = \frac{\sum_{k=1}^T K_h\left(F(t) - F(k)\right) X_k}{\sum_{k=1}^T K_h\left(F(t) - F(k)\right)} \tag{2.11}$$

where $K_h(x) = h^{-1}\phi(xh^{-1})$ with ϕ the density of the standard normal distribution and F is a time transformation taking into account the specific seasonality patterns for the risk factor to be modeled. The bandwidth h is chosen by increasing the optimal bandwidth found by leave-one-out cross validation until there are no more than a pre-specified number of local extrema in Y_t per year. For PV and wind forecasts as well as temperature, the extrema limit is set to four per year. The models for the individual risk factors differ in the choice of the functions $F(t)$, the exact way the errors are simulated, and whether the models yield hourly or daily time granularity. We use blockwise bootstrapping of the model residuals to generate simulations from our models.

We report an overview of the quality of the in-sample fit of the forecasts $(Y_t)_{t=1}^T$ in Table 2.1. The quality of the forecasts from the models is measured by the R^2 as a relative measure of fit and the in-sample mean absolute deviation (MAD) as an absolute measure of model error, which is complemented by the mean absolute percentage error (MAPE) as another relative measure of error. In the following, we discuss the specific stochastic models in detail.

	Control Zone	Frequency	R^2	MAD (MAPE)	Data Source
PV forecast	Tennet	hourly	88%	361 MW (27%)	tennettso.de
	50Hertz	hourly	81%	215 MW (37%)	50hertz.com
	Amprion	hourly	83%	244 MW (33%)	amprion.net
	Transnet	hourly	83%	169 MW (34%)	transnetbw.com
Wind forecast	Tennet	hourly	17%	1,455 MW (61%)	tennettso.de
	50Hertz	hourly	13%	1,464 MW (65%)	50hertz.com
	Amprion	hourly	20%	524 MW (61%)	amprion.net
	Transnet	hourly	8%	46 MW (87%)	transnetbw.com
Temperature	all	daily	78%	2.66° C (26%)	Mathematica
Gas price	all	daily	95%	0.37 EUR (1.6%)	NCG settlement prices
PV generation	Tennet	hourly	96%	196 MW (15%)	tennettso.de
	50Hertz	hourly	94%	106 MW (18%)	50hertz.com
	Amprion	hourly	92%	158 MW (21%)	amprion.net
	Transnet	hourly	92%	102 MW (20%)	transnetbw.com
Wind generation	Tennet	hourly	93%	367 MW (15%)	tennettso.de
	50Hertz	hourly	91%	428 MW (19%)	50hertz.com
	Amprion	hourly	83%	227 MW (26%)	amprion.net
	Transnet	hourly	82%	18 MW (34%)	transnetbw.com
Day-Ahead price	all	hourly	68%	6.74 EUR (16%)	EPEX day-ahead auction
Intraday price	all	hourly	85%	4.70 EUR (11%)	EPEX intraday average

Table 2.1: In-sample fit for the different models: comparing historic data $(X_t)_{t=1}^T$ and estimation/seasonal trends $(Y_t)_{t=1}^T$. MAD abbreviates mean average deviation and MAPE mean average percentage error.



(a) (b)

Figure 2.3: (a) Boxplots comparing the hourly PV in-feeds of the real data and a simulation in the Tennet control zone (circles means, bars medians). (b) Partial auto-correlation functions of the Tennet simulations and the original data till lag 48 h.

2.3.1 Day-ahead PV forecast

The amount of PV generation influences the volume the VPP can sell on the power market and, therefore, is a central variable in its business model. It is also an important factor influencing prices on the day-ahead market. However, since the actual generated volumes are not known at the time when the day-ahead market closes, the VPP sells the amount from the latest generation forecast $\hat{X}_t$. Therefore we model the day-ahead electricity prices to be dependent on these forecasts and base our models for actual PV generation on the generation forecast. We model PV forecasts separately for the four German network control zones based on the publicly available day-ahead PV forecasts published on the homepages of the four German grid operators. Data are available in 15-min time intervals, which we aggregate to an hourly time series.

Within the in-sample period, a significant amount of new PV capacities were installed. We account for this fact by transforming absolute generation into relative generation per MW capacity by dividing generation by installed PV capacity, which is available in daily time granularity for each of the four German control zones (Deutsche Gesellschaft für

Sonnenenergie, 2015). Modeling the output per installed capacity allows us to extrapolate into the future based on assumptions of future installed capacities. Since capacity data are incomplete between August 1, 2014 and December 31, 2014, we reconstruct the values in this time period by linear interpolation.

The series of PV in-feeds exhibits superimposing daily and yearly seasonality. To account for daily seasonality, we split the model into 24 hourly models, one for each hour of the day. To be consistent across season, we remove daylight savings from the data, by analyzing all data in winter time. For each hour h, we account for yearly seasonality by smoothing the data to a yearly pattern, that is, we estimate a season-dependent forecast $Y_{F(t),h}$ as described below. The function $F(t)$ is defined as the number of minutes between sunrise and sunset on day t, which rests on the assumption that the number of light minutes is a good explanatory variable for PV generation. We combine the 24 estimates for seasonality to one single estimate for a smooth yearly trend $\hat{Y}_t$. Our seasonal component in the exemplary Tennet zone has an R^2 of 88% and a MAD of 361 MW (27%).

To model the deviations from the trend, we consider a logarithmic error term

$$\epsilon_t = \log\left(\frac{\hat{X}_t + c}{\hat{Y}_t + c}\right)$$

to account for the heteroskedasticity in the data. Given the above, we can write

$$\hat{X}_t = (\hat{Y}_t + c)e^{\epsilon_t} - c$$

where $c > 0$ is a constant that is used to avoid $-\infty$ in the logarithm for night hours without any power generation.

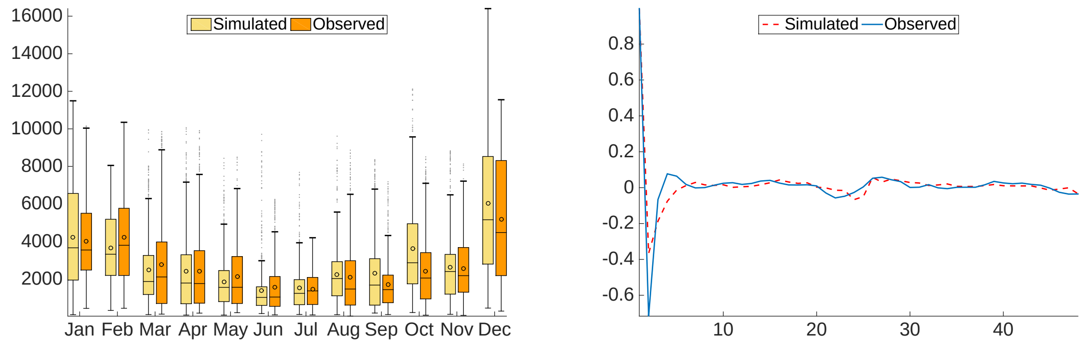
To generate samples from the model, we use blockwise bootstrapping with a block-size equal to one week by randomly drawing a block of 168 hourly residuals ϵ_t from our data (one residual from each model for each specific day in a week) and then use these resampled errors to simulate the process. To account for yearly variations within the errors, we separate the year in three periods and draw the respective error ϵ_t from past errors in that same period. As periods, we use winter (November–February), summer (May–August) and a transition period comprising March, April, September, and October. Blockwise bootstrapping ensures that the intraday serial correlation in the errors is preserved. Furthermore, it provides a non-parametric representation of the error term ϵ_t, which is clearly non-normal and also does not seem to conform to any other standard parametric distributional model.

To check whether the simulated PV forecasts exhibit the same distributional properties as the actual sequence, we compare simulations for the year 2014 with the actual empirical data. Figure 2.3 shows a comparison of monthly boxplots for hourly PV in-feed in the exemplary Tennet control zone, which is the zone with the most installed PV capacity[4]. The plot reveals that the distributions are close, in particular the means, medians, and quartiles are closely matched for most months. While most features of the distributions appear to coincide, the simulated data contain more extreme observations and therefore slightly more outliers. As this effect is only marginal, we do not expect it to distort our analysis. Figure 2.3 compares the empirical partial auto-correlation function (PACF) of a simulated trajectory for the year 2014 to the PACF of the actual data. Evidently, the two functions are very similar and agree in all their important characteristics. We conclude that the model captures the inter-temporal dynamics of PV in-feed reasonably well.

2.3.2 Day-ahead wind power forecast

Similar to the forecast of PV generation, the aggregator uses the previous day forecast of wind power generation to determine its bids on the day-ahead market. Hence, its fluctuations represents a substantial risk in the VPP's business model. Wind power forecasts are used as inputs for the power price models and the models for actual wind generation. We obtain the data from the same sources as the data on PV forecasts and

[4] Results for the other network zones look similar and are available on request.



(a) (b)

Figure 2.4: (a) Boxplots comparing the hourly wind in-feeds of the real data with a simulation in the Tennet control zone (circles means, bars medians). (b) Partial auto-correlation functions of the Tennet simulations and the original data till lag 48 h.

apply the same modeling approach, the only difference being that the function F is not the number of minutes from sunrise to sunset but the function

$$F(t) = \begin{cases} \frac{\lceil t/24 \rceil - b}{183} & b \leq t/24 \leq b + 183 \\ 1 - \frac{\lceil t/24 \rceil - b}{183}, & \text{otherwise} \end{cases} \tag{2.12}$$

where the parameter b, that is, the minimum of the function, is found by testing all values from 1 to 365 and selecting the value that leads to the best fit of the kernel regression estimate in terms of the highest correlation coefficient between historic data $\hat{X}_t$ and seasonal trend Y_t. This yields similar, but slightly different parameters b for the four zones. While Tennet has an optimal b of 362, that is, a function F with minimum value on December 28, 50Hertz has an optimal b of 360 or a minimum on December 26. Amprion and Transnet share the same optimal b at 359.

We find a significant yearly seasonality in wind energy forecasts. Our trend component for wind generation in July is 40%–50% below the corresponding value for January. As shown in Table 2.1, our seasonal component has an overall R^2 of 17% and a MAD of 1455 MW (61%) in the exemplary Tennet zone, which we selected as an example again because it has the largest installed wind capacity of the four German zones[5]. These measures show that the seasonality in wind generation is not as pronounced as in PV generation, which happens due to the relatively weak daily seasonality.

As with PV forecasts, the simulations of the wind generation forecast are created by blockwise bootstrapping from the seasonal residuals of the real data using weekly block intervals to preserve serial correlation. The errors are thereby added in the same sequence as for the PV generation forecasts to preserve correlation between the different generation assets. Figure 2.4 shows a good fit of our model to the 2014 data of the Tennet control zone.

2.3.3 Actual PV and wind power generation

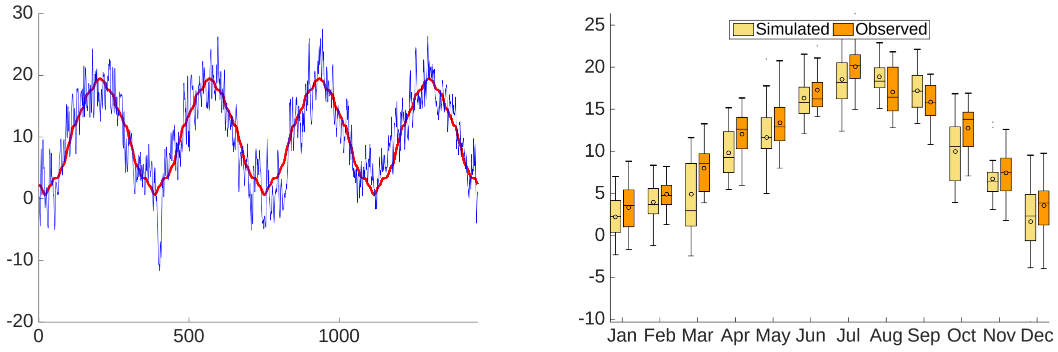
We model actual PV and wind power generation based on their day-ahead forecasts. While the forecasts are important for the day-ahead power price models, the actual generation enters the intraday price models and is used to calculate the VPP's generation and intraday balancing volumes. As for the forecasts, we use publicly available data provided by the four transmission system operators for our analysis.

We regress actual generation X_t against the respective forecasts $\hat{X}_t$, that is, estimate the following linear regression models

$$X_t = \beta_1 + \beta_2 \hat{X}_t + \epsilon_t. \tag{2.13}$$

To simulate actual generation in the out-of-sample period, we calculate the generation estimates from the above regression using the simulated PV or wind power forecast for that particular network zone as generated from the models in Sections 2.3.1 and 2.3.2. We bootstrap the error terms by randomly selecting residuals of the regression. In doing so, we do not differentiate between different periods of the year as we assume that the size of forecasting errors does not depend on the time of year.

[5] The results from the other zones look similar and are available on request.



(a) (b)

Figure 2.5: (a) Seasonal profile from kernel regression and the actual temperature time series over our regression period from 2011 to 2014. (b) Boxplots comparing real daily temperatures and their simulation in Germany (circles means, bars medians).

As shown in Table 2.1, the resulting R^2 for PV and wind power generation in the Tennet zone are equal to 96% and 93%, respectively. The mean absolute deviation is around 196 MW (15%) for PV and 367 MW (15%) for wind power generation.

2.3.4 Average daily temperatures

We model daily average temperatures as an input factor for the simulation of power prices. To construct a proxy for average daily temperatures in the EPEX market zone, we use a population weighted mean of all the Austrian and German cities with more than 10,000 inhabitants. The index is constructed using the Mathematica 7.0 functions *CityData* and *WeatherData* (Graf and Wozabal, 2013). As Figure 2.5 shows the temperatures follow a clear seasonal pattern with a minimum in the first month of each new year. We apply the same non-parametric modeling framework as to PV and wind energy forecasts, except that we model only average daily temperatures. We apply the same function F as in the case of wind forecasts and find $b = 22$, that is, a minimum of $F(t)$ on January 22 as optimal.

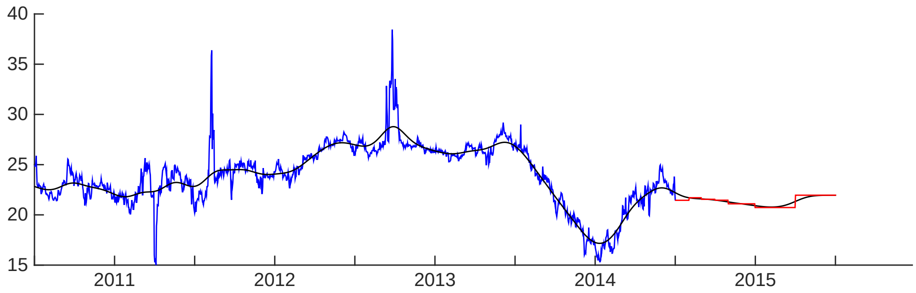


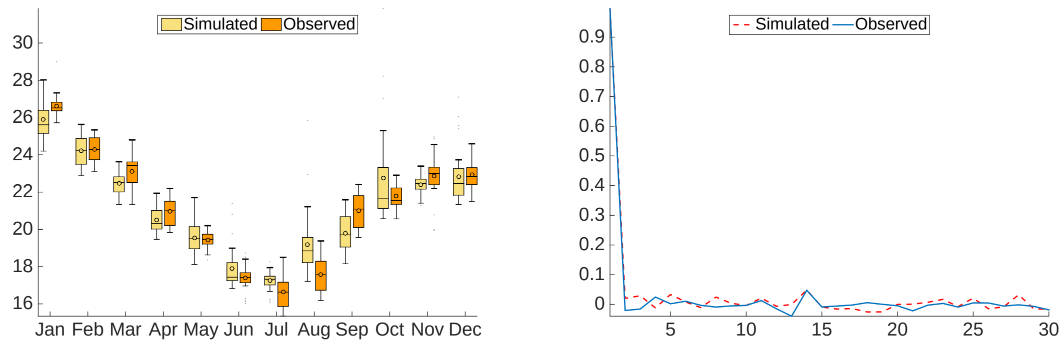
Figure 2.6: Actual EEX natural gas prices 2011–14 in EUR (blue line) and the gas futures prices in EUR for 2015 (red line) as traded on December 30, 2014. The black line shows the fitted means from kernel regression as input into our time-dependent mean reversion model.

To simulate the error we use blockwise bootstrapping from the set of seasonal residuals in the same sequence as in the PV and wind models. We use blocks of 7 days to preserve serial correlation from the same period of the year (summer, winter, or transition period). The resulting seasonal component is shown in Figure 2.5 panel (a) together with the actual temperatures. It has an R^2 of 78% and a mean average deviation MAD of 2.66° C. As in the case of PV and wind forecasts, simulation is conducted for the year 2014; the box plot in Figure 2.5 shows a good fit.

2.3.5 Natural gas price

The natural gas price enters our model as a covariate in the power price regression models. We use EEX's daily settlement prices for Germany's largest gas market zone NetConnect Germany (NCG). Prices are determined every day for the respective following day as average of all natural gas day-ahead contracts, which are in the order book during the daily settlement period.

The gas price simulation is based on a mean reversion process for logarithmic prices, which is a common choice for commodity markets, since it can be observed that in the long-run, commodity prices tend to be drawn back to their marginal production cost (Schwartz, 1997). We employ a mean reversion model which is a non-parametric discrete



(a)

(b)

Figure 2.7: (a) Boxplots comparing the real daily gas price and one of its simulations (circles means, bars medians). (b) Partial auto-correlation functions of the gas price simulations and the original data till lag 30 d.

time version of the model in Tseng and Barz (2002), who use a time-dependent mean. They describe the dynamics of the price process G_t in continuous time by the following stochastic differential equation

$$d\ln G_t = -\mu(\ln G_t - m_t)dt + \sigma dB_t, \tag{2.14}$$

where B_t is a Wiener process and m_t is the time-dependent mean. Tseng and Barz (2002) first deseasonalize the logarithmic prices by estimating m_t and then obtain the rest of the parameters by maximum likelihood estimation.

In line with the models for other risk factors, we use kernel regression to estimate the time dependent mean m_t. However, unlike the models treated so far, m_t does not follow a stable seasonal pattern over time. Therefore, we use a simple linear function $F(t) = t$ for the kernel regression. The lack of seasonal pattern also makes forecasts more difficult. Hence, instead of trying to forecast the corresponding Y_t for the year 2015 as we did in the other models, we use the observed futures prices on December 30, 2014 as the expected mean reversion levels for 2015. To generate a smooth transition between our in-sample period and the out-of-sample simulation period, we combine observed gas prices from

2011 to 2014 with futures prices and use the resulting 5-year time series to estimate m_t. We choose the minimal bandwidth h, which reduces the number of local extrema to 15 over all five years. The resulting gas price means are shown in Figure 2.6 as a black line. m_t captures the medium-term price patterns without short-term fluctuations and shocks. Additionally, Figure 2.6 illustrates the expected prices observed in the futures market and the corresponding futures means found by the kernel regression.

To estimate the parameter μ of the mean reverting model, we define $y_t = \ln G_t - \ln G_{t-1}$ and rewrite (2.14) in discrete time as

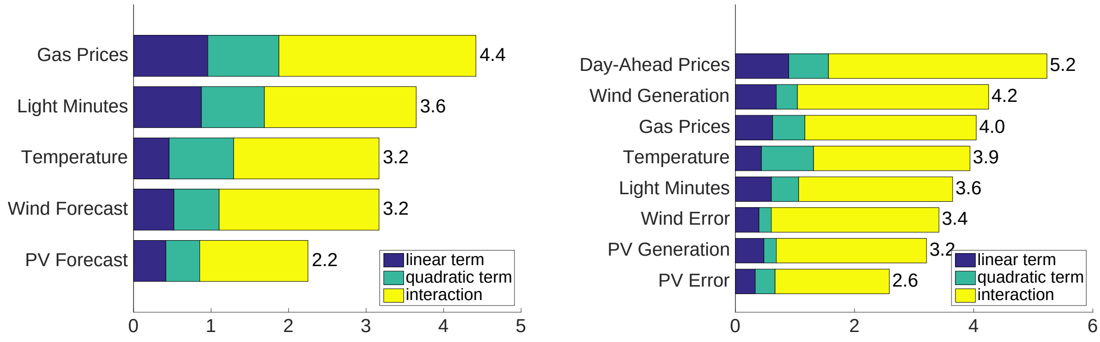
$$y_t = -\mu(\ln G_t - m_t) + \epsilon_t \tag{2.15}$$

which can be estimated via ordinary least squares regression. The mean reversion proves to be a very good fit: the R^2 is 95% and the MAD is at 0.37 EUR (1.6%).

The estimated residuals from the ordinary least squares model (2.15) are clearly non-normal. Following the ideas already applied to the other models, we capture the distributional characteristics of ϵ_t by bootstrapping the residuals of the regression model (2.15). Unlike the models for PV and wind power forecasts, we do not differentiate between seasons while bootstrapping. To assess the distributional properties of our model, we use the estimated means m_t to simulate prices for the year 2014 and compare them with the actual prices. Figure 2.7 illustrates the fit of this modeling approach. It also indicates that there is no auto-correlation to be captured, so we do not use block bootstrapping for this model.

2.3.6 Power prices

The simulation of day-ahead power prices is based on linear regression models using forecasts for renewable generation, daily temperatures, and natural gas prices. To model seasonal effects, we use the number of minutes between sunrise and sunset as an additional deterministic regressor. To capture daily seasonality, we estimate one model per hour and



(a) (b)

Figure 2.8: Number of times that each regressor was on average selected in each of our 48 day-ahead [panel (a)] and 48 intraday [panel (b)] power price models. The blue box quantifies average inclusions as linear factor, the green box as quadratic factor, and the yellow box as quadratic interaction with one of the other regressors. Theoretically, each regressor could be selected six times in each day-ahead model and nine times in each intraday model.

further differentiate between weekdays (Monday–Friday) on the one hand and weekends on the other. Therefore, finally we estimate 48 separate regression models describing the dynamics of the power price.

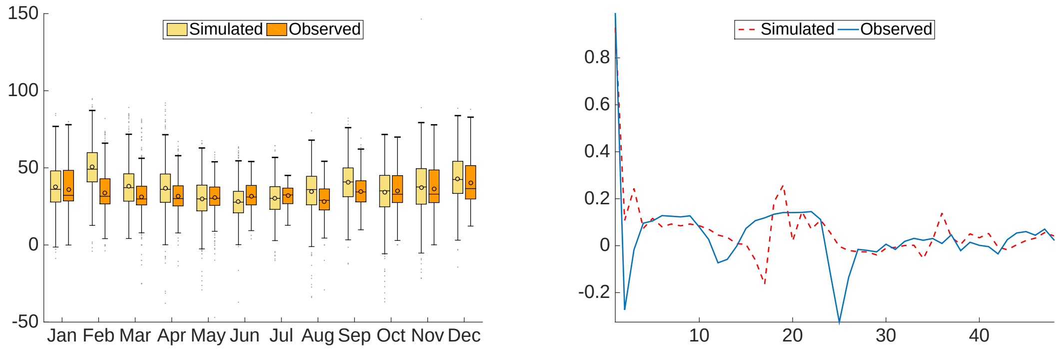
The intraday price is modeled similarly, except it uses actual wind power and PV generation (instead of forecasts) and forecast errors as additional regressors. The reason for this is that actual wind power and PV generation only become known during the time of intraday trading and we assume forecast errors to be a price driver on the intraday market, where renewable generators have to balance their position in the short term. Additionally the day-ahead price is included as a regressor in the intraday models.

We include all interactions of the regressors up to the second order. To ensure parsimony of the model, we performed stepwise combined forward-backward elimination as described in Draper and Smith (1998), Section 15.2, and used the Bayesian information criterion for model selection.

Hourly power price data were obtained from EPEX SPOT day-ahead and intraday markets for the German-Austrian price zone. The combination of selected regression models achieves an R^2 of 68% for day-ahead prices and 85% for intraday prices. Their MAD equals 6.74 EUR/MWh (16%) for day-ahead and 4.70 EUR/MWh (11%) for intraday prices. Keles et al. (2016) recently published a paper with specific focus on forecasts of German day-ahead power prices benchmarking an artificial neural network with more than 20 input variables (MAD of 4.67 EUR/MWh) against an ARIMA model (MAD of 8.84 EUR/MWh). Therefore, we conclude that the step-wise regression chosen for this research is well suited to model power prices in our context.

Each day-ahead model consists on average of 17.6 regressors and each intraday model of 31.3 regressors using 1,460 data points each. Figure 2.8 demonstrates how often certain regressors have been selected on average in our regression models. The relative importance of the factors is similar in day-ahead and intraday models. For day-ahead models, the most important regressors are gas prices and deterministic lighted minutes, which can be considered a proxy for yearly seasonality. For intraday models, the day-ahead price is the most important regressor by far. It is followed by wind generation in the respective hour, the gas price, and temperatures. Interestingly PV forecast errors or actual generation are selected significantly less. This could originate from PV's superior predictability and, therefore, lower intraday volume in comparison to wind generation, as well as its correlation with light minutes (see Section 2.3).

We simulate electricity prices using the above regression models to forecast the electricity price using the simulated values for the regressors as input. To simulate the errors, we bootstrap the in-sample residuals from the regression models using blockwise bootstrapping with block size of 24 h to preserve serial correlation. To assess the fit of our model's distributional properties, we use simulated prices for the year 2014 based on simulated regressors for 2014 and compare them with the actual prices. Figure 2.9 shows that the distributional characteristics are captured well by our models.



(a) (b)

Figure 2.9: (a) Boxplots comparing the real hourly day-ahead power prices and one of its simulations (circles means, bars medians). (b) Partial auto-correlation functions of the power price simulations and the original data till lag 48 h.

2.4 Results

In the following, we apply our portfolio optimization algorithm to 5,000 scenarios with 8,760 h each, which we generate from our stochastic models described in Section 2.3. We thereby make the assumption that the PV and wind forecasts and generation in the four German network zones are representative for groups of assets that an actual VPP can potentially hold in its portfolio. The CVaR parameter α is set to 1%[6].

We analyze the characteristics of our individual assets' and portfolios' yearly revenues π based on the simulations for the year 2015. For the simulation of prices, we require a simulation of the overall PV and wind power generation. We therefore scale up the forecasts by the projected overall capacity. To do so, we assume a continuation of the capacity growth trend for PV and wind generation. More specifically, we use the estimates provided in the review of the Renewable Energy Sources Act from August 1, 2014. The bill states a growth target of 2.5 GW per year both for PV and wind. We further assume

[6] Optimizations with α at 3%, 5%, and 10% showed similar results and conclusions. They are available on request.

the same relative growth rate over all German control zones. This leads to an expected capacity increase in our exemplary Tennet control zone of 0.99 GW (6.5%) in PV and 1.01 GW (6.7%) in wind capacity.

Throughout this section, revenues are denoted in EUR per expected MWh of generation as discussed in Section 2.2. This unit price allows for a good comparison between different assets or portfolios. Variations in revenue for a single scenario, therefore, can be either due to generation volumes that differ from the forecast or due to price variations.

We estimate expected revenue $E(\pi)$ as well as its standard deviation σ_π and calculate Sharpe ratios as a relative risk measure. Additionally, we calculate the CVaR of the individual assets and portfolios.

First, we analyze the characteristics of the eight individual PV and wind assets, including their interdependencies. Then, we present the portfolio optimization results for our main model with full volume and market risk and for the two model variants discussed above. Wherever applicable, we discuss three example portfolios with different levels of risk aversion: the minimum-risk, medium-risk/return, and high-return portfolio[7]. In each section, we also derive implications for VPPs and their participants. Using second-order stochastic dominance, we find that *every* risk-averse decision maker would prefer our exemplary medium-risk/return portfolio to an unmanaged market portfolio, regardless of the actual risk preferences.

2.4.1 Individual asset performance

We find that yearly revenues differ considerably in their distributional characteristics: first, between the wind and the PV group of assets and, second, between the different assets in each of those two groups. Results are reported in Table 2.2. The average

[7] Note that we do not assume any of these three levels of risk aversion to be indicative of the risk aversion of a real VPP. Consequently, we exclusively use these portfolios to discuss the range in which profits and risks vary with varying levels of risk aversion.

		$E(\pi)$	σ_π	Sharpe	CVaR
Individual	Tennet	30.67	0.88	35.02	28.23
PV assets	50Hertz	31.50	1.19	26.56	28.38
	Amprion	31.86	1.08	29.48	29.06
	Transnet	31.70	1.12	28.31	28.71
Individual	Tennet	33.42	1.72	19.48	29.04
wind assets	50Hertz	32.42	1.93	16.78	27.51
	Amprion	34.25	1.98	17.30	29.24
	Transnet	35.23	3.87	9.10	26.13
VPP with	Average German	32.98	2.27	14.51	29.13
volume and	Minimum risk	32.61	0.63	51.95	30.99
market risk	Medium risk/return	33.92	1.60	21.17	30.04
	High return	35.23	3.87	9.10	26.13

Table 2.2: The expected yearly revenue $E(\pi)$, its standard deviation σ_π, and the resulting Sharpe ratio as well as its Conditional Value-at-Risk (CVaR) for the base case model. All (except the Sharpe ratio) are noted in EUR per ex ante expected MWh per year.

wind assets' expected revenue is 2.4 EUR/MWh higher than for PV assets (33.8 vs. 31.4 EUR/MWh). This 7.6% revenue difference is surprisingly high considering both energy sources are producing the same commodity for the same market, only at different times. The lowest wind asset's revenues (50Hertz Wind) are still higher than the highest revenues for a PV asset (Amprion PV). This difference is particularly interesting, because PV's expected revenue has historically been higher than the one for wind. This was the case as PV's generation is strongly positively correlated with the power demand and, therefore, with historical prices. The difference decreased greatly over the recent past. While it was on average 18.6% in 2011, it decreased to 3.1% in 2014. Our forecast shows that in 2015 the revenue for PV is expected to fall below that for wind. The reason for this development is the stronger temporal concentration of PV power generation within a few hours of the day. This leads to lower wholesale prices in these hours, when the market share is rising. This effect outweighs the correlation with power demand and has been predicted in the literature (Hirth, 2013).

Additionally, we find that expected revenues between different assets within the PV and within the wind group vary significantly. For example Transnet wind is around 8.7% more valuable than 50Hertz Wind. One of the reasons is the difference in installed capacity: by the end of 2014 Transnet had the least wind capacity with 0.65 GW while 50Hertz had 15.1 GW. Generation from a specific control zone is temporally concentrated; thus, a higher generation volume from a particular zone has a negative effect on price level. This is the same relationship that leads to an overall decrease in the price levels for PV and wind assets.

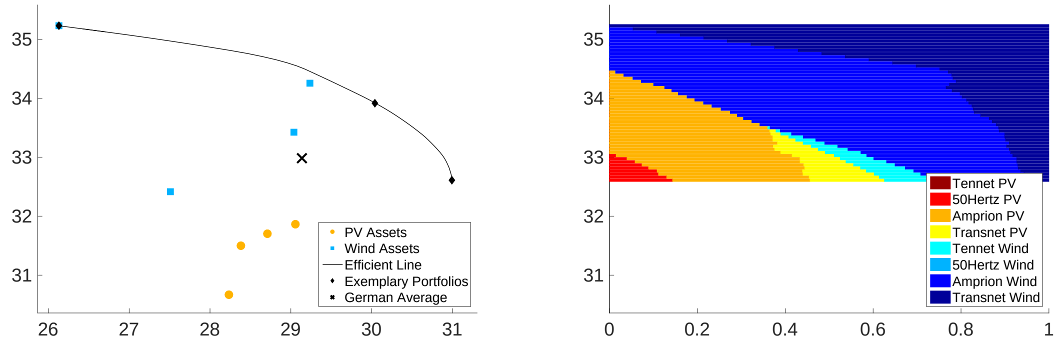
The difference in expected revenue between PV assets is not as pronounced as between wind assets. The most valuable PV asset (Amprion PV) earns only 3.9% more than the least valuable one (Tennet PV). Hence, on the one hand, we observe that a higher market share has a more pronounced negative effect on PV's than on wind's expected revenue. On the other hand, it leads to a smaller divergence of PV revenues across network zones compared to that of wind revenues.

Important conclusions for the VPP business model can be drawn from the relative revenues. The differences imply that some assets are significantly more attractive in a portfolio than others, even without considering risk. DM service providers, therefore, have good reasons to apply location- and technology-dependent pricing schemes, which are still uncommon in the industry.

Higher risks are associated with higher expected revenue from wind assets. Its average standard deviation is more than twice higher than for PV (2.4 vs. 1.1 EUR/MWh). Overall, PV assets' revenues show significantly higher Sharpe ratios. The Tennet PV asset has the highest Sharpe ratio of 35, although it has the lowest expected revenue. One reason for this might be the large geographic size of the Tennet control zone, which offers a natural diversification effect. The other PV zones are relatively homogeneous, with ratios between 26 and 29. Wind assets, on the contrary, show Sharpe ratios between 9 and 19. The lowest value represents the high-risk/high-return outlier Transnet wind. It has the highest expected revenue of all assets, but also a disproportionally higher standard deviation. A possible reason for these uncommon distributional characteristics can be that the zone has by far the least installed wind capacity of all and therefore provides higher obtained prices as discussed above as well as a lower natural diversification effect. The other three wind assets are relatively homogeneous, with Sharpe ratios between 17 and 19.

Interestingly, the individual assets' CVaRs are more homogeneous than their expected revenues. They vary between 26.1 EUR/MWh (Transnet Wind) and 29.2 EUR/MWh (Amprion Wind). Moreover, PV and wind assets do not significantly differ as wind assets' higher risk apparently compensates its higher expected revenue. On average, the CVaR is 17.3% below the expected revenues for wind and 9.0% for PV assets. A stylized calculation example helps to illustrate the effect of these levels on a fixed cost business model: we compare the asset owner's expected annualized results with results for the 1% CVaR case. When assuming 80% debt financing, capital costs for equity twice as high as for debt and an operational expenditure cost share of 29% (Fraunhofer IWES, 2015b), debt service makes up 47% of expected revenues. In this setup, a revenue reduction of 17.3% (as in the 1% CVaR case) translates into a profit reduction of 73% for the equity owner in a particular year. Considering that typical asset owners in this industry are rather risk-averse (e.g., yield cos, pension funds, private individuals), any potential to reduce this risk by diversification is relevant.

For a potential diversification effect, the correlation between the individual assets' yearly revenue is of particular interest. We find a negative correlation of every wind with



(a) (b)

Figure 2.10: (a) Individual assets' expected revenue (x-axis) and their respective CVaR (y-axis) with squares and circles in EUR/MWh, as well as the efficient line of portfolio combinations, including the three portfolios selected for further analysis with diamonds. Additionally, the cross marks the average German direct marketing portfolio at the end of 2014. (b) The respective asset weights of the portfolios on the efficient line.

every PV asset. On average, the correlation coefficient between the two technologies' revenues is -0.31. Hence, a good wind year is likely to be a poor sun year and vice versa. This obviously has a positive effect on diversification potential between these assets. Within each generation technology, the correlation between revenues is positive. The average correlation coefficient is 0.58 among PV assets and 0.72 among wind assets.

2.4.2 Portfolio diversification in a VPP

There is substantial opportunity for risk diversification, and a superior risk/return combination can be achieved by efficient portfolios of renewables. Portfolios on the efficient frontier clearly dominate the individual assets' risk/return profile. The efficient frontier as well as portfolio compositions are depicted in Figure 2.10.

We discuss three distinct portfolios on the efficient line whose risk/return characteristics are given in Table 2.2. The highest return portfolio is achieved by simply building a portfolio solely from the asset with the highest expected revenue, which in our case is the

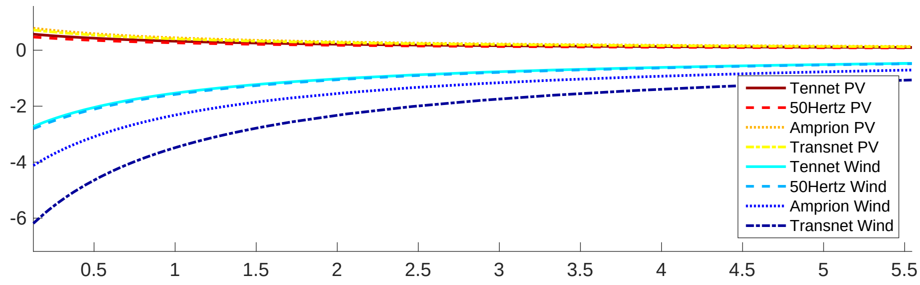


Figure 2.11: Premia/discounts or the difference between respective asset's market and portfolio value in EUR/MWh for different levels of risk aversion λ (on the x-axis).

wind generation asset in the Transnet control zone. It is very profitable, but also highly risky. The minimum-risk portfolio dominates all individual PV assets as it has a higher expected revenue and higher CVaR. It consists of three PV and three wind assets though PV provides 60% and wind 40% of the expected power generation. The portfolio's CVaR is higher than that of any individual asset by a wide margin of 1.8 EUR/MWh and its CVaR is only 5% below its expected revenue (compared with more than 25% for the highest return portfolio).

The medium-risk/return portfolio is defined as having the expected revenue exactly between the high-return and the minimum-risk portfolios. It offers higher revenues than all individual assets, except the two most profitable ones, while its CVaR is still higher than that of any individual asset. Compared with the two more profitable wind assets, its CVaR is 15% and 3% higher. These two wind assets provide almost 80% of the portfolio's expected generation. However, the addition of 20% PV generation ensures a significantly less risky position. As a result, the portfolio CVaR is only 11.4% below its expected value, which is a substantially better ratio than that for the high-return portfolio or for any other wind asset.

The willingness to pay for additional capacity to be included into the portfolio, or an asset's *portfolio value*, was defined in Section 2.2.3. Our results show that it varies significantly from the asset's *expected revenue* and also between different levels of risk aversion. Figure 2.11 shows the different assets' premia and discounts depending on the level of risk aversion λ. The four PV assets receive a premium, whereas the four wind assets are discounted. This discount is particularly high for the most risky wind asset *Transnet Wind*. As expected, a higher level of risk aversion, that is, a smaller value for λ, corresponds to higher absolute values of premia and discounts.

To illustrate the potential value of our results, we benchmark the medium-risk/return portfolio to the average German direct marketing portfolio. As illustrated in Table 2.2, the medium-risk/return portfolio has a 2.9% higher expected revenue and a 3.1% higher CVaR. Furthermore, we tested our medium-risk/return portfolio for second-order stochastic dominance (De Giorgi, 2005; Koppa and Chovanec, 2008) and found that it indeed dominates the average German DM portfolio consisting of a mix of all eight assets in proportion to their DM participation in reality. This result establishes that the optimal portfolio is preferable to the market portfolio regardless of the VPP's risk preferences.

A typical German VPP with an average asset mix selling 5 TWh of power per year, would thereby have 4.7 million EUR lower expected revenue per year and 4.6 million EUR lower CVaR. Hence, it is valuable for asset owners to actively and carefully select VPP partners to optimally diversify their risks.

2.4.3 Model variant I: portfolio diversification from the operator's perspective

So far, we have considered the perspective of the VPP as a whole. Now we consider the perspective of a VPP operator who optimizes the composition of renewables in his direct marketing portfolio. He guarantees prices to the capacity owners based on Equation (2.5) while setting his service fee f equal to 1 EUR/MWh, which is roughly the average in the German VPP market in 2015 (Edwardes-Evans, 2015). In this setup, the operator carries not only the entire market risk but also part of the volume risk. With resulting gross margins, the operator needs to cover his remaining fixed costs for trading operations,

		$E(\pi)$	σ_π	Sharpe	CVaR
VPP operator perspective	Average German	1.00	0.80	1.25	-1.87
	Minimum risk	1.00	0.73	1.37	-0.98
VPP with fixed feed-in tariffs	Average German	30.00	3.07	9.75	25.60
	Minimum risk	30.00	0.74	40.48	28.14

Table 2.3: Portfolio outcomes for our two variations of the base case model in Sections 2.4.3 and 2.4.4: First, from the zoomed-in VPP operator perspective and, second, with the VPP receiving fixed feed-in tariffs. The reported data points have the same definition as in Table 2.2.

asset owner-oriented sales force and administration.

The operator's expected revenue is fixed at 1 EUR/MWh. Its standard deviation is similar among the different assets but very large compared with the operator's expectation, leading to Sharpe ratios around 1. The assets' CVaRs show a significant possible loss between -1.5 and -2.4 EUR/MWh. Average 1% CVaR is at -1.6 EUR/MWh for PV and at -2.3 EUR/MWh for wind assets. We can conclude that for the VPP operator, risk is much more severe than for the VPP as a whole. Quoting a fixed unit price and, thereby, carrying full market risk can induce actual losses, not just reduced interest on equity. Therefore, the analysis of diversification potential is even more important for the VPP operator than for the individual asset owner.

Table 2.3 shows two distinct portfolios from the operator's perspective: the average German direct marketing portfolio as discussed above and the portfolio with minimum risk for the VPP operator. The results show that the operator's CVaR in absolute terms can be increased by 0.89 EUR/MWh – almost by as much as his expected gross margin. Relatively, his negative CVaR can be reduced by 48% compared with the average DM portfolio and by 60% compared with the riskiest individual asset. The optimal portfolio consists of two PV (50Hertz, Transnet) and one wind asset (Amprion).

Hence, differentiating the pricing between asset owners is highly important to the

VPP operator (as described in Section 2.4.1). However, it is not sufficient to do so based only on the assets' different expected revenues but also based on their risk patterns. Otherwise the VPP is likely to end up in a significantly inferior risk/return position.

2.4.4 Model variant II: portfolio diversification without market access

Around the world, large numbers of renewable assets are either not required or not able to participate in wholesale markets. The most common sources of revenue for these assets are feed-in-tariff subsidy schemes or power purchase agreements (PPAs). In these schemes the asset owner is eligible to receive a fixed price per generated unit of power. In that case, the owner does not carry any market risk. His remaining source of uncertainty is, therefore, the overall power volume his asset will generate. Next, we model possible portfolios consisting of these fixed price assets.

We assume a uniform feed-in tariff of 30 EUR/MWh for all assets. We picked this amount to make our analysis comparable with Section 2.4.2. In our setup the owner receives the guaranteed tariff for his *actual* generation and does not have to worry about forecasting and resulting balancing penalties. Therefore, we calculate the VPP revenues as the product of actual generation and tariff (see Equation (2.7)).

As in the model settings with market risk, we find a substantial risk diversification effect for assets that are receiving feed-in tariffs; the results are reported in Table 2.3. While for the average German portfolio, the CVaR falls 14.7% below its expected revenue, this difference is only at 6.2% in the case of minimum risk. This means that the minimum-risk portfolio dominates all individual assets or other portfolio combinations because there are no differences in expected revenues. Therefore, risk minimization maximizes overall utility. The benefits of the minimum-risk portfolio become even more obvious while analyzing the standard deviation of the two different portfolios, which is four times higher in the average German portfolio than in the minimum-risk portfolio. The optimal portfolio consists of six assets: all four PV assets and two wind assets (Tennet and Amprion). Roughly three-quarters of the portfolio generation is expected to come from PV and only one-quarter from wind.

Our results clearly show that optimal pooling of renewables is relevant for all asset owners and is not dependent on the option or the requirement to sell directly in the wholesale market. Even in cases where pooling is not necessary to enable direct marketing by providing economies of scale through shared transaction costs, there is a rationale to build larger, renewable portfolios.

2.5 Conclusion

Efficient risk mitigation strategies that address the inherent price and volume risks that owners of renewable generation capacities face on liberalized electricity markets are essential for the successful global roll-out of PV and wind power generation. This paper investigates the new question, to what extent pooling different technologies as well as different locations in the portfolio of a virtual power plant can reduce aggregate risk. We confirm our hypothesis that there exists a substantial risk diversification potential. Therefore, VPPs should choose their portfolio not only based on the characteristics of individual technologies and locations but also by paying close attention to the interdependencies of these assets. Doing this allows the same level of expected return at a significantly improved risk profile or vice versa. This result holds true for assets, which are pooled already to sell their generation on the power market through a VPP, as well as for assets, which receive a fixed compensation per unit and, therefore, are not necessarily pooled yet.

For *existing VPPs*, our results imply that they need to carefully consider their pool composition in order to capture the potential for an improved risk/return profile. This requires an in-depth analysis of assets' expected revenues and risks as well as their interdependencies. For the average German VPP, this should result in an increased share of PV assets, which are, for the most part, not yet included in direct marketing schemes due to their small average size.

One approach to affect pool composition is developing *appropriate risk/return sharing mechanisms* among different VPP participants. This process will likely be moderated by the VPP operator. Today every participant carries its volume and market risk itself even after entering a direct marketing portfolio. Therefore the value from diversification is not captured, although an institutional collaboration already exists. Sharing of volume risk among VPP participants is only possible, if their revenue depends on installed capacity, not on generated volume. How respective transfer price and risk sharing mechanisms can be designed in detail is a question for further research.

By developing a technology- and location-specific pricing scheme, VPPs would fully assume their intermediary role as a transmission mechanism between asset owners and the central market. This would put increased value on renewable generation that is located at sights with less cyclical generation patterns and will reduce medium-term volume risk in the system. Thereby VPPs could render an, often called for, location-based differentiation of subsidy schemes unnecessary.

We find substantial risk diversification potential for assets, which receive a *fixed feed-in tariff* per unit. We see two ways in which these assets can capture the additional value. First, our results shed light on *optimal firm or portfolio size*. They provide a clear indication that there is a benefit in larger and diversified portfolios in contrast to holding individual assets. The most obvious form of such diversification is likely to be integrated ownership and operations of a large and carefully chosen portfolio of assets. Of course, this also provides additional economies of scale effecting operations and maintenance costs.

Second, there are also other more organizationally loose approaches for risk diversification of renewable assets. For instance, one can imagine a simple *insurance contract* for asset owners without additional features such as joint trading. An insurance provider, who builds a portfolio using the results in this paper, should be able to cover the owner's revenue risk for a significantly lower premium than it would be required for the isolated individual revenue risk.

Furthermore, it becomes clear that owners of renewables have an additional incentive to pool their generation rather than just fulfilling regulatory requirements or cashing in on extra feed-in tariffs. The diversification effect, which the asset owners can receive from a VPP, mitigates their transaction costs from operations on the power market. If this value is captured, then the need for additional compensation or incentives for the owners will be reduced. This *stronger alignment of the regulator's and owner's objectives* needs to be taken into account in policy discussions regarding the market premium model. Consequently, the additional premium for DM participants could potentially be lowered as risk diversification incentivizes them to join anyways.

Next to more detailed work on transfer pricing mechanisms, we see three other research areas that would expand our work: (1) more markets, (2) more geographies, and (3) more technologies. First, our model setup could be expanded to include operations on the *balancing market*, which results in additional costs as well as additional revenues. On the one hand, VPPs have to pay penalties for the deviation between their actual generation and their last forecast (30 min before the intraday market closes). On the other hand, in the future they also are likely to sell capacity on the balancing market.

Second, renewable revenues could be pooled *across national or even continental borders*. The potential of this broader geographic diversification can be analyzed with our model setup and a suitable data set.

Third, it is an open question, which *other future asset classes* VPPs should include in their portfolios. Possible candidates are different flexibility options, such as combined heat and power plants, demand-side management, and storage capacities. These other assets provide different risk patterns than PV and wind assets and could provide the VPP with a chance to enhance its overall risk/return position even further.

Chapter 3

An Equilibrium Pricing Model for Wind Power Futures

written in collaboration with Prof. Dr. David Wozabal

Generation from wind power plants is uncertain and affects profits of wind power generators and conventional generators alike. Currently, generators have limited options for transferring the resulting wind-related volume risks. The European Energy Exchange (EEX) recently introduced exchange-traded wind power futures to address this market imperfection. We propose a stylized equilibrium pricing model featuring two representative agents and analyze equilibrium prices as well as the mechanics behind risk premia for wind power futures. We calibrate and simulate stochastic models for wind power generation, power prices, electricity demand, as well as other relevant sources of uncertainty and use the resulting scenarios to conduct a case study for the German market, analyzing prices, hedging effectiveness, and risk premia. Our main result suggests that wind generators are willing to pay an insurance premium to conventional generators to reduce their risks.

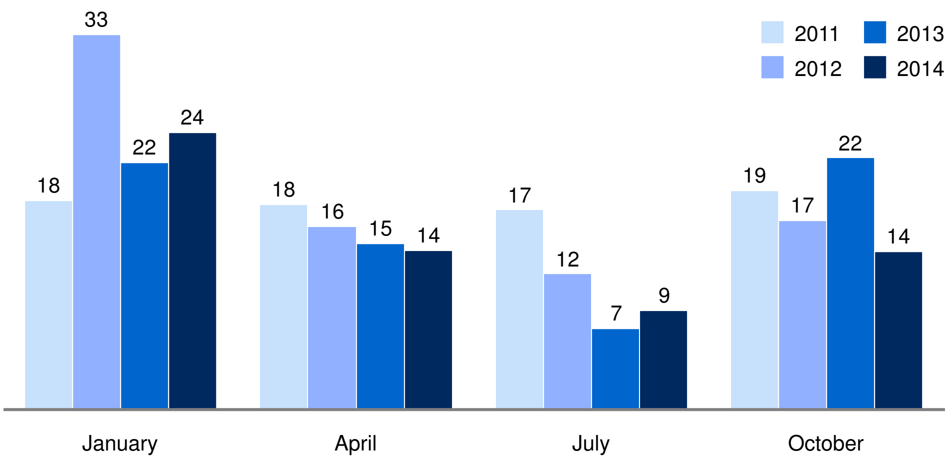


Figure 3.1: German monthly wind capacity factors 2011–14 in percent for four example months January, April, July and October. Generation data in 15-min intervals were obtained from the four German transmission system operators 50Hertz, Amprion, Tennet, Transnet, and daily capacity data from Deutsche Gesellschaft für Sonnenenergie (2015).

3.1 Introduction

The energy industry has historically been one of the most weather-sensitive sectors in the economy as temperatures throughout the year drive the demand for power and natural gas. This situation has been greatly exacerbated by heavy investment into weather dependent renewable energy generation in the recent years, which is instrumental in reducing future greenhouse gas emissions. Variable power generation technologies such as wind power and photovoltaic constitute the major share of current renewable installations, and projections indicate their continued growth in the future (IEA, 2014).

In some countries, such as Germany or Denmark, the share of wind power has already reached considerable levels. This development has introduced substantial weather risks to the supply side of the energy industry resulting from stochastic wind speed, which defines wind power generation volume in any particular period. Figure 3.1 displays capacity factors, defined as ratio of average generation volume over installed capacity, illustrating that wind generation in Germany is highly volatile even for longer observation periods such as months and years.

The resulting volume risk faced by owners of wind power plants is currently not tradable via standardized products on energy exchanges. Consequently, wind power producers cannot sell their volume risk to other market participants who might be more ready to take it, inducing inefficiencies and ultimately welfare losses. For this reason, *wind power futures* have recently been proposed by the European Energy Exchange (EEX). The underlying of these futures are capacity factors for the average German wind power plant, that is, the risk-neutral prices for a contract are naturally bounded between 0 and 100. The holder of the futures receives a payment that is equal to the actual observed utilization in a given month, quarter, or year. Consequently, the planned futures can act as an instrument to hedge risks emanating from volatile wind generation volume.

In this paper, we investigate the determinants of the price of these futures contracts and the structure of potential risk premia in the market. The answer to this question is highly relevant to wind power and conventional generators, as well as every other agent with an interest to trade wind futures. In our analysis, we seek to estimate expected payoffs accurately and try to understand potential risk premia.

There essentially exist three distinct streams of literature concerned with pricing futures contracts: applications of the rational expectation hypothesis (REH), no-arbitrage pricing, and equilibrium models. The REH states that the price of a futures contract is equal to the discounted expected spot price, or in the case of wind power futures, the expected capacity factors in Germany (see Burger et al., 2004; Fleten and Lemming, 2003, for examples of models for power futures). The REH assumes risk-averse decision makers and therefore precludes risk premia whose existence in power markets is well established (Huisman and Kilic, 2012; Kolos and Ronn, 2008; Longstaff and Wang, 2004; Redl and Bunn, 2013; Weron, 2008).

No arbitrage pricing approaches on the other hand, identify a risk-neutral probability measure and an associated market price of risk. Hence, they do consider risk premia but cannot explain their mechanics and interaction with the position holders' business model.

Furthermore, the underlying of wind power futures is not tradable until maturity. Hence, no arbitrage pricing approaches based on replication arguments are not directly applicable (see Eydeland and Geman, 1999; Pirrong and Jermakyan, 1999, for the structurally similar case of power futures).

A detailed analysis of risk premia's size, structure, and drivers is possible with equilibrium models. Equilibrium models capture the fundamental economic rationale of risk-averse market participants, which allows to explain their trading behaviour and the resulting premia (Allaz, 1992; Allaz and Vila, 1993; Bessembinder and Lemmon, 2002; Bushnell, 2007; Bushnell et al., 2008).

Consequently, as this model class is best suited for our analysis, we develop an equilibrium model for wind futures valuation to understand prices and risk premia. More specifically, we adapt the model by Bessembinder and Lemmon (2002), who analyze the equilibrium between two representative agents on the power market. To the best of our knowledge, the present paper is the first application of an equilibrium model to the valuation of a weather derivative. Thereby, this paper links two disjoint bodies of literature and contributes to the overall understanding of pricing derivatives without a tradable underlying. In our case, the two representative agents are defined as the owner of a wind power plant and a conventional generator. In the resulting mean-variance expected utility framework we can define utility-maximizing futures positions in dependence on the futures price. These optimal supply curves allow us to derive a closed form solution for the futures' equilibrium price and quantity.

As the proposed wind power futures will be introduced in Germany, we use the German market in our simulation-based case study. However, the proposed methods and fundamental results are of a general nature and carry over to other countries as well.

We use our model to determine the sign of the wind futures' risk premia as well as the determinants of these premia in a thorough sensitivity analyses. We find that wind power futures are likely to be traded at a discount for a broad range of input assumptions, that is, the wind power producer is ready to sell the contracts at a price below the expected capacity factor, leaving the conventional producer with an expected profit from the transaction.

We conduct an extensive sensitivity analysis to explore the range of prices and discounts that might arise in the market for wind futures. Additional contributions are the examination of the hedging effectiveness for exemplary wind generators and a detailed analysis and simulation of wind capacity factors as the underlying risk factor.

The paper at hand is structured in six sections. Section 3.2 describes the role of wind-related risks in the energy industry and the proposed wind futures. Section 3.3 discusses the chosen equilibrium model including the agents' profit functions. Section 3.4 gives details on the underlying simulation models and data assumptions for our case study. Section 3.5 reports model results regarding equilibrium prices, premia and quantities as well as sensitivity analyses. Section 3.6 concludes the paper.

3.2 Wind-related risks and the new wind power futures

3.2.1 Players, their risks, and the need for wind power futures

This paper focuses on two groups of firms that are strongly affected by volatile wind generation: *wind power generators* and *conventional generators*. The former profits from more wind power generation while the latter profits from less wind power generation as will be argued in the following.

For *wind power generators*, uncertainty in wind generation volume manifests in three distinct forms of risk. First, pre-investment forecasts of long-term wind speeds could be wrong resulting in volumes consistently below the expected level over the whole lifetime of the investment. Secondly, risk is induced by medium-term volatility of wind power generator's volume from period to period. Lastly, wind power producers active on power exchanges face the short-term risk of committing wrong quantities on the day-ahead market resulting in balancing costs. In this paper, we focus on the second type of medium-term risk that is concerned with revenues for several weeks to a maximum of three years.

With 75% of wind power plant costs being upfront capital expenditures and usually a high level of debt, stable revenues are essential for generators. Additionally, most of the investors are looking for a low risk profile (yield cos, pension funds, cooperatives etc.). As most generators worldwide do not (only) participate in wholesale markets, but receive a fixed compensation per generated unit of electricity, such as a feed-in tariff, volume risk is more important than price risk. The same is true for subsidy schemes with a floating market price premium. Correspondingly, in a recent survey of renewable energy companies, 45% of respondents state that weather-related volume risk has materialised in their business (Watts, 2011). Hence, it is plausible that wind power generators would be natural sellers of wind power futures.

Conventional generators are the second group of firms who are affected by volatile wind power generation. In a power system with limited export potential the conventional generator's profit is negatively correlated with wind generation volume for two reasons. First, the more power is generated from wind power plants, the less power is generated conventionally as marginal costs of coal or gas power plants are higher than of wind power plants. Second, wind generation volume has a negative correlation with power prices. Hence, in the case of high wind power generation, the conventional generator not only produces less volume overall, but also receives a lower price on his remaining generation volume. Consequently, conventional producers would be natural buyers for wind power futures.

Why firms generally hedge risks is still a question of scientific debate. Possible reasons include optimization of a convex tax schedule, non-diversifiable shareholders, or costs of debt during financial distress (Golden et al., 2007). Regarding weather risk, there is recent evidence that hedging has a positive impact on firm value (Perez-Gonzalez and Yun, 2013). In the case presented here, in which conventional generators and wind power generators profits are negatively correlated, it seems obvious to transfer some of this risk between the two, and thereby, lower the risk exposure of both (Golden et al., 2007).

Currently, however, most wind power generators do not hedge their risk from volatile wind power generation. In fact, weather-related risk is the least transferred risk for renewable energy companies. Insurance contracts are chosen by 9% of companies, special purpose vehicles by 7% and financial derivatives by 1%. A lack of awareness of weather markets and the lack of affordable solutions for smaller plants is stated as the number one barrier to more active risk management (Watts, 2011).

Summarizing, an accessible liquid market for wind derivatives does currently not exist although wind power and conventional generators have an increasing need to transfer wind risks.

3.2.2 Wind power futures as new hedging instrument

The *EEX* will launch a new exchange-traded wind power futures in 2016 (EEX, 2016). *Nasdaq OMX*, otherwise mainly active in the Nordic and UK market, has also included a German wind power futures in their contract portfolio (Nasdaq OMX, 2015). Both companies started this product category in Germany as it has a power market with large installed wind capacities of more than 40 GW as of 2015 (Reuters, 2016). Our discussions with EEX have revealed that there is substantial interest in this new product category from a broad set of market participants including wind and conventional power generators, but also direct marketing providers and reinsurance companies[1].

The proposed wind futures fall into the category of weather derivatives. Such derivatives also exist for temperature, humidity, rainfall, snowfall, and stream flow. The above-mentioned initiatives are not the first attempts to establish a market for wind deriva-

[1] Personal conversation with Dr. Maximilian Rinck of EEX on September 15, 2016

tives. In 2007 the US Futures Exchange announced its launch of wind futures in seven U.S. regions, but trading never picked up. Alexandridis and Zapranis (2013) state that difficulties in accurately modeling wind generation and valuing wind derivatives were the main reason for slow growth in this segment. This emphasizes the importance of a good understanding of the markets as a prerequisite for the success of any financial product.

The *payoff function* for the holder of wind power futures at maturity T is given as

$$\tilde{F}^T = \frac{100}{H} \sum_{h=1}^{H} \tilde{W}_h, \tag{3.1}$$

where $\tilde{W}_h$ represents the wind capacity factor in hour h and H the total number of hours within the *measurement period*, which might be a month, a quarter, or a year. Note that $\tilde{W}_h$, and therefore also $\tilde{F}^T$, are uncertain at time of trading ($t = 0$).[2] The capacity factors W_h are measured for the whole German market zone, that is, represent the average utilization of wind power stations across Germany.

The proposed wind futures provide the opportunity to hedge pure volume risk in wind power generation. They do not include a price component such as classic power futures. Contracts, are settled financially and do not entail the purchase of *green power* as they are not linked with a guarantee of origin certificate or the like.

To illustrate how wind futures work, we discuss a typical trading and settlement process: A wind power generator sells wind futures for the current market price. He locks in this value before the measurement period begins. After the measurement period, the futures realization is calculated based on the wind index published by EEX. If the actual capacity factor is higher than the locked in price, the wind power generator has to pay his futures position's excess realization. But at the same time he also receives more revenue for his higher wind power plant's generation volume. If the actual capacity factor is lower, his generation revenues are also lower, but he receives an excess payment for his futures position. Hence, variability of profits, and therefore risk, reduces. The

[2] As a convention, we use a tilde to denote random quantities.

conventional generator is a likely buyer of wind futures. Hence, all her cash flows are opposite to the wind power generator's and she as well is able to lower her wind-related profit risks by engaging in the transaction.

The described transaction between wind power and conventional generator could also be performed directly over the counter (OTC) but standardization via an exchange offers higher transparency and lower transaction costs as well as a decreased credit risk.

The central disadvantage of exchange-traded contracts is the typically higher basis risk for the individual hedger. This is the case if the underlying wind index and the generation from the hedger's portfolio are not perfectly correlated (Golden et al., 2007) as we will demonstrate in Section 3.5.1. Overall, the combination of wind risk's increasing relevance in the energy industry and the introduction of wind futures by EEX and Nasdaq OMX could create a first liquid market for exchange-traded wind derivatives.

3.3 Market model

This section gives a detailed definition of our equilibrium model. For reason of completeness, we review Bessembinder and Lemmon (2002), which forms the basis of our model, in Section 3.3.1. We discuss the agents' utility and abstract profit function, optimal futures position, and conditions for an equilibrium. The adaptation of the model to wind power futures is explained in Section 3.3.2. In Section 3.3.3, the definition of the agents' specific profit functions are detailed.

3.3.1 An equilibrium model for power futures

The model of Bessembinder and Lemmon (2002) is based on three assumptions.

1. The market participants are homogeneous enough to be aggregated into two representative agents – one with a natural short position and one with a natural long position.

2. The agents' expected utility is linearly dependent on their expected profit and its variance. This assumption holds true if the utility function is quadratic or if the returns are distributed according to an elliptic distribution (Chamberlain, 1983). Even if these conditions are not fulfilled, the mean-variance approach seems to be a fairly good approximation of expected utility (Markowitz, 2014).

3. Both agents possess the same information including the distribution of wind capacity factors in the futures' measurement period.

According to assumption 2 above, both agents' expected utility in dependence on their profit $\tilde{\pi}$ is expressed as

$$\mathbb{E}(U(\tilde{\pi})) = \mathbb{E}(\tilde{\pi}) - \frac{\lambda}{2} \operatorname{Var}(\tilde{\pi}). \tag{3.2}$$

The parameter λ defines the agents' attitude towards risk – if λ is zero, the agent is risk-neutral, while $\lambda > 0$ implies risk aversion.

The agents' profits $\tilde{\pi}$ are defined as sum of two parts: the profits from their general business operation $\tilde{\rho}$ called *but-for-hedging profits* and the profits from potentially holding a futures position ρ

$$\tilde{\pi}^{W,C} = \tilde{\rho}^{W,C} + Q^{W,C}(F^0 - \tilde{F}^T). \tag{3.3}$$

where Q is the futures position, decided upon in $t = 0$, and the superscripts indicate the agent (wind power producer W or conventional producer C). If Q is positive, the agent sells a futures contract at $t = 0$ and receives Q times the market price F^0. At maturity she pays Q times the realization $\tilde{F}^T$ to her counterpart. If Q is negative, the agent buys a futures contract and all signs are reversed.

The optimal quantities for the two agents can easily be derived from the first order conditions of the utility maximization problem as

$$Q^{W,C} = \frac{F^0 - \mathbb{E}(\tilde{F}^T)}{\lambda^{W,C} \operatorname{Var}(\tilde{F}^T)} + \frac{\operatorname{Cov}(\tilde{\rho}^{W,C}, \tilde{F}^T)}{\operatorname{Var}(\tilde{F}^T)}, \tag{3.4}$$

where the first term is called *speculative position* and the second term is called the *hedging position.*

The *speculative position* is the same for both agents. It represents the quantity of futures they are willing to sell or buy when the current futures price F^0 deviates from their expected futures realization $\mathbb{E}(\tilde{F}^T)$. If the futures price exceeds the expected realization, they would sell futures and vice versa. The smaller the agent's individual risk aversion or the variance of the futures price, the greater the speculative position. Building on our assumption that there is no information asymmetry on futures realization, both agents' speculative position have the same sign, that is, from the speculative positions alone, there would be no trades in the market.

This situation is resolved by a non-zero *hedging position* in (3.4). The term is different from zero if there is a correlation between the agent's but-for-hedging profits $\tilde{\rho}$ and the futures realization $\tilde{F}^T$. In that case, a futures position can reduce the agents' risk. Note that the hedging position is affected by the variance in the futures realization, but it does not depend on the agent's risk aversion.

We introduce the following market clearing condition

$$Q^W + Q^C = 0, \tag{3.5}$$

which implies that there exists an equilibrium, if the agents take the exact opposite position of each other.

3.3.2 Model adaptation to wind power futures

Combining equations (3.1), (3.4) and (3.5), it is easy to see that the unique equilibrium price F^{0*} in EUR/H is equal to

$$F^{0*} = 100\ \mathbb{E}(\tilde{W}) - \xi \left(\mathrm{Cov}(\tilde{\rho}^W, \tilde{W}) + \mathrm{Cov}(\tilde{\rho}^C, \tilde{W})\right),\ \text{with}\ \xi = 100\frac{\lambda^W \lambda^C}{\lambda^W + \lambda^C}, \tag{3.6}$$

where

$$\tilde{W} = H^{-1}\sum_{h=1}^{H} \tilde{W}_h$$

represents the average wind capacity factor over the futures' measurement period.

The formula for the equilibrium futures price consists of two terms. The first equals the risk-neutral value of the futures contract $\mathbb{E}(\tilde{F}^T)$. Therefore, the second term of Equation (3.6) defines the risk premium that depends on ξ and the covariance of both agents' but-for hedging profits $\tilde{\rho}^{W,C}$ with the average wind capacity factor $\tilde{W}$. In line with the qualitative description in Section 3.2, we hypothesize that the wind power generator's covariance is positive and the conventional generator's covariance is negative making the wind power producer a net seller of futures and the conventional producer a net buyer. We will empirically test this in Section 3.5.

If neither of the agents is risk-neutral and the covariances of $\tilde{\rho}$ with $\tilde{Q}$ do not cancel out, that is, $\mathrm{Cov}(\tilde{\rho}^W, \tilde{W}) \neq -\mathrm{Cov}(\tilde{\rho}^C, \tilde{W})$, then there exists a nonzero premium on the wind futures market. Its sign depends on the two covariance terms. Intuitively, the agent whose payoffs exhibit a higher absolute covariance with the wind generation has a higher hedging demand and is willing to pay a premium or accept a discount on the expected price. In our model, if the wind power generator's absolute covariance is higher, the futures sells at a discount and if the conventional generator's absolute covariance is higher, the futures sells at a (positive) premium.

3.3.3 "But-for-hedging" profit functions of representative agents

In this section the agents' but-for-hedging profits are defined and described. Note that for our purpose it suffices to model the components of the agents' profits that are correlated with the wind capacity factor $\tilde{W}$, since other components – particularly fixed costs – do not affect the price of the wind futures.

Let P^W be the deterministic compensation that the wind power generator receives per unit of generated power in the measurement period. The assumption of deterministic compensation is in line with subsidy schemes for wind generation around the world, which are mostly guaranteed fixed feed-in tariffs for a certain time span (KPMG, 2015). Define the *wind power generator's total but-for-hedging profits* in the measurement period as

$$\tilde{\rho}^W = P^W \sum_{h=1}^{H} K_h \tilde{W}_h, \tag{3.7}$$

where K_h represents the total wind generation capacity in the asset owner's portfolio, which in our case equals the whole system-wide wind generation capacity. Hence, $K_h \tilde{W}_h$ yields the system-wide wind power generation in hour h.

Because of near zero marginal production costs of renewables, the second representative agent in our model – the *conventional generator* – has to cover the system load $\tilde{D}_h$ net of wind production and photovoltaic (PV) generation $\tilde{G}_h^{PV}$,

$$\tilde{R}_h = \tilde{D}_h - K_h \tilde{W}_h - \tilde{G}_h^{PV}, \tag{3.8}$$

called residual load. Note that PV generation is negatively correlated with wind power generation and therefore mitigates some of the volume risk for the conventional generator, which has a direct impact on his demand curve for wind futures.

To calculate the but-for-hedging profits of the conventional generator, we assume that he can neither transfer produced energy in time, that is, store it, nor geographically to sell it on another market. Hence, all the energy produced at time t has to be sold instantaneously. This assumption is realistic for our case study market Germany as interconnector capacities are fully utilized for most hours of the year.

We assume that for some b_h the generators cost function in hour h equals (Bühler and Müller-Merbach, 2007)

$$\text{Cost}_h = b_h \frac{\tilde{R}_h^o}{\mathbb{E}(\tilde{R}_h)^{o-1}} \tag{3.9}$$

with the parameter $o \geq 2$ controlling the convexity of the function. The parameter b_h allows us to fit the cost function to historic spot price data with its time-dependency allowing for seasonal variation. The estimation of b_h and assumptions on the order o are detailed in Section 3.4.2.

	R^2	MAD (MAPE)	Source
Wind Generation	16%	3,361 MW (62%)	Transmission system operators
PV Generation	87%	872 MW (28%)	As for wind generation
Power Demand	55%	5,613 MW (10%)	ENTSO-E (2016)
Day-Ahead Power Price	74%	6.29 EUR (15%)	EPEX day-ahead auction

Table 3.1: In-sample fit of trend components in the different simulation models – comparing real and forecasted values. MAD abbreviates mean absolute deviation and MAPE mean absolute percentage error. Data for renewable generation is sourced from transmission system operators 50Hertz, Amprion, TenneT, Transnet.

The agent generates revenues by selling the residual load to power retailers on the power exchange receiving a randomly fluctuating, hour-specific spot market price $\tilde{P}_h^C$. Based on the above, we model the conventional generator's but-for-hedging profits $\tilde{\rho}^C$ in the measurement period as

$$\tilde{\rho}^C = \sum_{h=1}^{H} \tilde{P}_h^C \tilde{R}_h - b_h \frac{\tilde{R}_h^o}{\mathbb{E}(\tilde{R}_h)^{o-1}}. \tag{3.10}$$

3.4 Econometric model and case study

3.4.1 Simulation of underlying random variables

The proposed market model is based on four random variables. The wind capacity factor $\tilde{W}_h$ enters directly into the pricing Equation (3.6) and both profit functions. PV generation $\tilde{G}_h^{PV}$, system-wide power demand $\tilde{D}_h$, and spot power price $\tilde{P}_h^C$ enter solely in the conventional generator's profits (3.10). All four variables have hourly granularity denoted with subscript h.

The random dynamics are simulated in S scenarios with H hourly intervals over the measurement period of the respective futures contract. Hourly granularity is necessary to capture distributional characteristics of the agents' profit functions correctly. Individual scenarios are denoted with subscript s, replacing the tilde used so far to indicate the random nature of a quantity. The number of scenarios S is set to $5,000$ throughout.

The stochastic models are fully non-parametric and taken from Gersema and Wozabal (2016). Therefore, we only give a brief overview of the models and refer to Gersema and Wozabal (2016) for more details. The focus of the models is not only to provide forecasts for the random variables, but to capture their distributional properties over longer periods of time. Hence, our models differ from the usual short-term forecasting models that have been developed for power markets. All models are estimated using data from 2011–14.

The modeling and simulation process roughly consists of the following two steps:

1. A seasonal trend component is estimated using locally constant kernel regression. By forecasting capacity factors of wind power and PV generation, the trend can be extrapolated into the futures by incorporating expected capacity additions during the time frame in question. One daily trend times series is estimated for wind power generation and 24 distinct hourly time series for PV generation and power demand to capture their daily seasonality.

2. Hourly realizations are simulated by blockwise bootstrapping hourly deviations from the deterministic trend and adding the generated samples to the forecast levels. Random selection of the residuals is done in blocks of one week to preserve serial correlation and from one of three seasons (summer, winter, transition) to account for yearly variations in the errors.

We report the in-sample fit of our models in Table 3.1. The seasonal trend for PV generation and power demand has substantially higher predictive power than the one for wind generation. This is in line with our previous results on the high level of uncertainty in wind generation. Although the predictive power of the trend component is relatively weak for wind power, Figure 3.2 illustrates that its distributional properties are captured well.

Day-ahead power prices $\tilde{P}_h^C$ are simulated based on a linear regression model with six distinct input variables. These include the three random variables incorporated directly in the equilibrium model plus the following three, which are also simulated each individually as described in the following.

1. *Daily temperature* has a strong influence on energy prices and is incorporated as population-weighted mean of all the Austrian and German cities with more than 10,000 inhabitants. It is modeled and simulated with the same approach as renewable generation and demand in daily resolution.

2. *Daily prices for natural gas* are used as a proxy for prices of primary energy carriers. Their behavior is modeled with a mean-reverting process with non-constant mean reversion level, see Gersema and Wozabal (2016) for details.

3. The deterministic number of *minutes between sunrise and sunset* is used as a proxy for yearly seasonality in the power price regression model.

In all we estimate a total of 48 power price models, one for each hour and differentiated between weekend and work days. The regressors are determined using forward-backward model selection from a set consisting of the six variables described above, an intercept, as well as all quadratic interaction terms, to account for non-linear dependencies. The combination of the 48 regression models achieves a reasonably good fit, as reported in Table 3.1. It is used to forecast prices using the simulated values for the various regressors as input. Based on this forecasts price scenarios are simulated by blockwise bootstrapping from the regression models' in-sample residuals with a block size of 24 h to preserve serial correlation and adding these to the predicted price levels.

3.4.2 Data and assumptions

EEX and Nasdaq OMX introduce wind futures for yearly, quarterly, monthly, and weekly measurement periods. We select the monthly futures for our analysis for the following

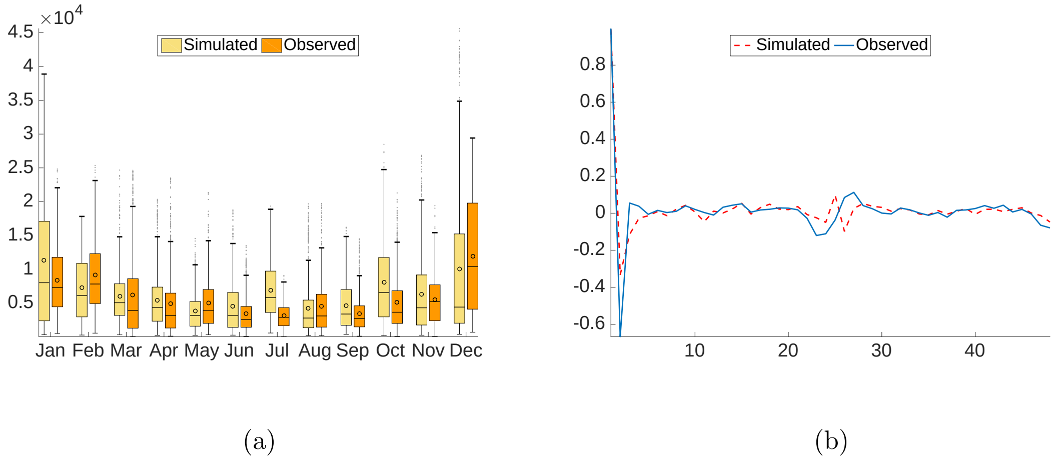


Figure 3.2: (a) Boxplots comparing the actual hourly wind in-feeds with the simulated distributions (circles means, bars medians). (b) Partial autocorrelation functions of the simulations and the original data up to a lag of 48 h.

three reasons:

1. The yearly and quarterly futures are cascaded automatically into monthly futures. They do not cascade further into weekly futures, but are settled after the monthly measurement period is over. This makes it likely that monthly futures will be the product with the highest liquidity.

2. The network operators pay the renewable subsidy down-payments to wind power generators in monthly frequency. The same frequency is typical for debt service. One month is therefore also a reasonable time frame for hedging purposes. This likely also supports liquidity in monthly futures.

3. The monthly period allows to analyze seasonal variations in equilibrium prices and premia.

More specifically, we select wind futures for the months of *January, April, July and October* as representative of the four quarters of 2015 for further analysis. The year 2015 is chosen in order to ensure continuity with our in-sample data spanning from 2011 to 2014. Therefore, the trading date ($t = 0$) is set to December 31, 2014.

The fixed feed-in tariff P^W per unit of wind power generation factors into the but-for hedging profits $\tilde{\rho}^W$. It is set to the average unit compensation in Germany, which was at 109.5 EUR/MWh in 2014. This compensation includes pure feed-in tariffs, but also market premia and direct marketing revenues. In Germany the fixed feed-in tariff has – since 2012 – been gradually replaced by a floating market premium that is paid on top of spot prices, matching revenues with the average feed-in tariff paid in the German market zone. Consequently, this does expose individual assets to price risk, the *average* German asset, however, still receives a fixed compensation at the same level as the former feed-in tariff.

The installed German wind capacities K_h for all hours h during the measurement period are required for the wind generator's profit function. The installed wind capacity in Germany on December 31, 2014 equals 37.3 GW. For 2015, we assume a continuation of the capacity growth trend using the estimates provided in the review of the German Renewable Energy Sources Act from August 1, 2014. The bill states a growth target of 2.5 GW per year and we assume that this additional capacity is added linearly throughout 2015 (Bundesministerium für Wirtschaft und Energie, 2014).

The conventional generation cost function is fit to historic data for the German market by estimating the time dependent parameter b_h in (3.9) using the approach proposed in Bühler and Müller-Merbach (2007). In particular, the parameter b_h is set so that the marginal costs of generating the expected residual load $\mathbb{E}(\tilde{R}_h)$ in a specific hour h are equal to the expected spot price $\mathbb{E}(\tilde{P}_h^C)$ in this particular hour, that is,

$$\frac{\partial\,\mathrm{Cost}_h}{\partial R_h}\bigg|_{R_h=\mathbb{E}(\tilde{R}_h)} = o b_h \frac{\mathbb{E}(\tilde{R}_h)^{o-1}}{\mathbb{E}(\tilde{R}_h)^{o-1}} \stackrel{!}{=} \mathbb{E}(\tilde{P}_h^C) \tag{3.11}$$

Hence, setting the cost parameter $b_h = \mathbb{E}(\tilde{P}_h^C)/o$ specifies the model correctly. As proposed by Bühler and Müller-Merbach (2009), we apply a cost function of fourth order ($o = 4$) in our base case. In the subsequent sensitivity analysis the order is varied, testing for changes in the shape of the merit order curve.

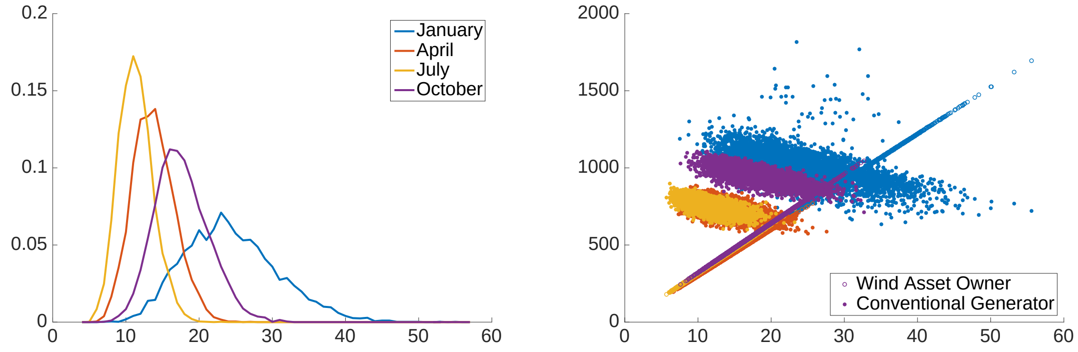
Our model framework would allow us to estimate the agents' risk aversion parameters

$\lambda^{W,C}$ from observed futures prices. However, since historical prices are not available, we have to assume risk aversion parameters for our simulation. For portfolio optimization with relative returns, typical risk aversion parameters are chosen between 2 and 4 (Fabozzi et al., 2007). To translate this ratio to our agent's monthly profit levels, we set $\lambda^{W,C} = 10^{-8}$ as a base case assumption. This assumption is based on the findings in Table 3.3, which identifies the wind power generator's expected profit $\mathbb{E}(\pi^W)$ in a range between 760 million EUR in January to 373 million EUR in July. For the same months his profit risk measured in standard deviation $\sigma(\pi^W)$ varies from 194 to 73 million EUR. At the assumed base case risk aversion level of $\lambda^W = 10^{-8}$, each EUR of variance in the agent's typical monthly profit is therefore weighted roughly two to seven times as high as a EUR of expected profit. Hence, his risk aversion is in a similar range as it is typically used for relative returns (Fabozzi et al., 2007).

Please note that the base case assumption is only a starting point for the analysis. It allows us to reliably analyze the sign and structure of risk premia, but not their absolute size. Hence, to enhance our understanding of the effect of different risk parameters $\lambda^{W,C}$, we vary their level in the sensitivity analysis.

3.5 Results and discussion

The following section discusses numerical results on the hypothetical wind futures market in 2015. We start by investigating the issue of *hedging effectiveness* in Section 3.5.1 and then turn to discussing simulation results obtained by applying our model to the German market using data and assumptions from Section 3.4. The distributions of wind capacity factors and the agents' but-for-hedging profits are discussed in Section 3.5.2 and Section 3.5.3, respectively, while the results on equilibrium prices, premia and quantities for our base case are reported and interpreted in Section 3.5.4. Subsequently, we conduct various sensitivity analyses with regard to changes in the three central determinants of risk premia: the agents' risk aversion and the two agents' but-for-hedging profit functions.



(a)

(b)

Figure 3.3: (a) Simulated distributions of average wind capacity factors in the four example months. (b) Clustered (by k-means) but-for-hedging profits $\rho^{W,C}$ of the two representative agents in million EUR, which result from these average wind capacity factors. Both panels are based on a simulation of 5,000 scenarios.

3.5.1 Hedging effectiveness

Wind power futures allow wind producers to hedge their volume risks. However, since the payoff is based on the capacity factors for the whole of Germany, the hedging effectiveness varies with the correlation of the producers capacity factors with the overall utilization of wind power plants.

More formally, writing the relationship between the random capacity factor $\tilde{W}_i$ of a single wind power producer i and the whole market zones capacity factor $\tilde{W}$ as a linear relation, we get

$$\tilde{W}_i = \alpha + \beta \tilde{W} + \epsilon.$$

The coefficient β specifies the linear relationship between the two random quantities and can be estimated by OLS regression as

$$\beta = \frac{\mathrm{Cov}(\tilde{W}_i, \tilde{W})}{\mathrm{Var}(\tilde{W})}.$$

Analyzing the above formula, we see that in the case, when $\tilde{W}_i$ and $\tilde{W}$ have exactly the same utilization patterns, that is, $\mathrm{Cov}(\tilde{W}_i, \tilde{W}) = \mathrm{Var}(\tilde{W})$, $\beta = 1$, implying that the two quantities exhibit exactly the same changes *on average*. Hence, in this case, the futures contract represents a good hedge for the wind power producers volume risk *on average*. We can go one step further by analysing the variance of error term, that is,

$$\begin{aligned}\operatorname{Var}(\epsilon) &= \operatorname{Var}(\tilde{W}_i - \beta\tilde{W}) = \operatorname{Var}(\tilde{W}_i) + \beta^2 \operatorname{Var}(\tilde{W}) - 2\beta \operatorname{Cov}(\tilde{W}_i, \tilde{W}) \\ &= \operatorname{Var}(\tilde{W}_i) - \frac{\operatorname{Cov}(\tilde{W}_i, \tilde{W})^2}{\operatorname{Var}(\tilde{W})}\end{aligned}$$

Clearly, in the case outlined above, $\operatorname{Var}(\epsilon) = 0$, that is, the hedge works perfectly *almost surely*. As the correlation gets weaker and β gets smaller, the uncertainty about the relation between $\tilde{W}_i$ and $\tilde{W}$ increases, which is signified by a growing $\operatorname{Var}(\epsilon)$.

Correspondingly, an owner of a diversified German wind portfolio with $\beta = 1$ can fully hedge his position against weather-related volume risks. If the portfolio's wind power generation is not perfectly correlated with the German average, β deviates from 1 and the wind future does not offer the opportunity to fully hedge against weather-related volume risks, which will also result in relatively smaller positions of the futures contract.

The yearly β of the entire wind production in the Amprion control zone, for instance, is equal to 0.79. The Tennet and 50Hertz control zone portfolios, which make up the majority share of German wind power capacity, have βs of 0.97 and 1.00, respectively. β for the Transnet portfolio in the Southwest of Germany is at 0.58. Hence, it is not optimal to hedge Transnet risk exposure with EEX's wind futures.

The above demonstrates that while wind futures are a valuable addition to the market, making volume risk tradable for wind power producers, the effectiveness of this instrument heavily depends on the correlation of the output with the overall German wind power output. Hence, for portfolios with a very small correlation with the wind power production in the German market zone, it might be preferable to buy tailor-made hedging contracts on the OTC market.

	Mean/Exp.	Median	Std.Dev.	CV
January	24.9	24.4	6.4	26%
April	14.3	14.1	2.8	20%
July	11.8	11.7	2.3	20%
October	18.1	17.9	3.7	20%

Table 3.2: Characteristics of the simulated distribution of average wind capacity factors over all hours of the four selected example months in percentage points. They are equivalent to monthly futures realizations $\tilde{F}^T$ in EUR/H (see Equation (3.1)).

3.5.2 Distribution of wind capacity factors

The simulation of hourly wind generation allows us to analyze the distribution of monthly wind capacity factors in detail. They are equivalent to futures realizations in EUR/H and the two terms are used synonymously in the following. Some characteristics of their distributions are reported in Table 3.2 for the selected example months[3].

The expected wind capacity factors exhibit a strong seasonal trend throughout the four example months. While the winter month January has the highest expected wind utilization with 24.9%, the summer month July only has an expected utilization of 11.8%; roughly 47% lower. Wind capacity factors in April and October are expected to fall between the two extremes.

The seasonal differences in expected wind yield are reflected in its standard deviation as well. It is highest in winter and lowest in summer. However, the effect is disproportionate as the coefficients of variation (CV) reveal. They indicate that not just absolute but also relative risk is higher in winter than in summer.

Figure 3.3 panel (a) shows simulation results for the four monthly wind capacity factors built from 5,000 simulated scenarios. It confirms that the summer distribution is substantially more concentrated around its expectation, while the winter distribution is

[3] Results for other months are available on request.

		Mean/Exp.	Median	Std.Dev.	CV	Corr.Coeff.
Wind asset owner	January	760	744	194	26%	1.00
	April	429	424	85	20%	1.00
	July	373	369	73	20%	1.00
	October	581	572	117	20%	1.00
Conventional generator	January	1,007	1,008	102	10%	-0.63
	April	725	725	46	6%	-0.57
	July	747	748	39	5%	-0.60
	October	947	948	51	5%	-0.71

Table 3.3: Characteristics of the simulated distribution of total but-for-hedging profits in million EUR over the four selected example months.

spread out over more than 30 percentage points. The distributions for April and October are in between the two, but clearly distinct from each other. The fact that the capacity factor's median is smaller than its mean indicates that its distribution is positively skewed.

3.5.3 Agent's but-for-hedging profits

In this section, we analyze interdependencies between the agents' but-for-hedging profits and wind capacity factors, which drive risk premia. The wind power and the conventional generator's but-for-hedging profit ρ_s^W and ρ_s^C for each scenario s are shown in Figure 3.3, (b) and Table 3.3 for the four example months.

Per definition, the wind power generator's but-for hedging profits are perfectly positively correlated with wind capacity factors. The higher the wind capacity factor, the more power and revenue the asset owner generates. The slope changes slightly between the different months due to increases in expected installed wind capacity throughout 2015.

The conventional generator's but-for-hedging profits are negatively correlated with wind capacity factors. The greater wind power generation, the lower conventional power generation and the lower are conventional profits. Higher wind generation also coincides with lower power prices, having an additional negative effect. Figure 3.3 graphically confirms this negative relationship between wind generation and conventional profits and Table 3.3 reports correlation coefficients between -0.57 for April and -0.71 for October. There are two reasons why simulated conventional profits are not a linear function of wind load as for wind power generators. First, the other three random variables add additional uncertainty. Second, the conventional generator has a non-linear (convex) cost function, implying that average capacity factors cannot be translated directly into average costs.

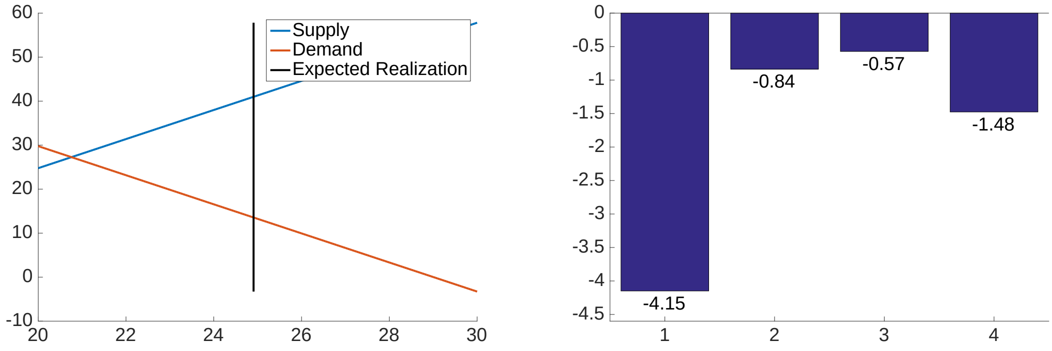
Table 3.3 also reports more details on the distribution of but-for-hedging profits themselves. The resulting coefficients of variation are substantially lower than for the wind power generator, indicating that on a monthly level the wind induced risk is less for the conventional generator than for the wind power producer.

3.5.4 Expected futures price, premium and quantity

In this section the results on equilibrium prices, premia and quantities are reported for the set of base case assumptions. These results are our best estimator for future market outcomes once trading is opened. Figure 3.4 displays both agents' optimal futures position and their intersection for example month January.[4]

Both curves are linearly dependent on price. The wind power generator's supply of wind futures increases with higher prices and the conventional generator's demand for them decreases with higher price. In the case of the January futures 2015, the equilibrium price is at 20.76 EUR/H with a quantity of 27 thousand contracts being traded. Panel (a) of Figure 3.4 also displays the expected wind capacity factor during January 2015 as a vertical line, marking the risk-neutral valuation of the wind futures at 24.91 EUR/H.

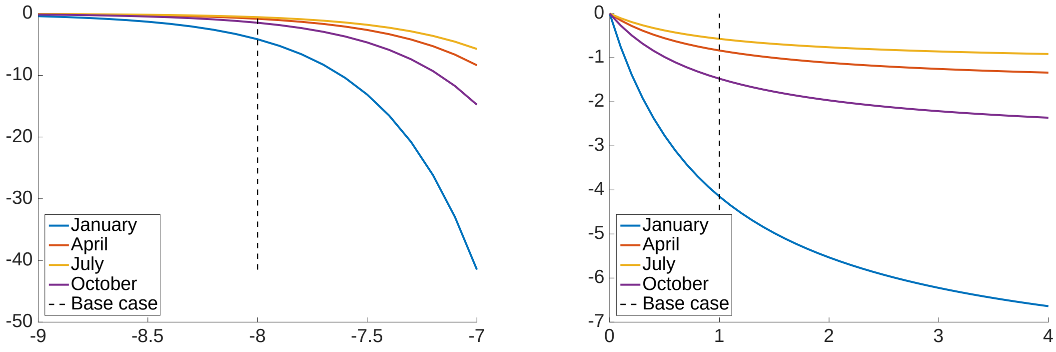
[4] Note that we change the sign of the conventional generator's supply function, making it into a demand function to facilitate the illustration.



(a) (b)

Figure 3.4: (a) Supply curve (wind power generator) and demand curve (conventional generator) of wind futures for January 2015 depending on current futures price F^0 (x-axis). Quantity is denoted in thousands on the y-axis. The intersection marks the equilibrium price and quantity. Furthermore the black vertical line represents the expected futures realization $\mathbb{E}(F^T)$. (b) Discounts $(F^0 - \mathbb{E}(F^T))$ for the wind futures of January, April, July and October 2015.

The difference to the obtained equilibrium price is the risk premium, which in this case is negative. The wind power generator is willing to accept a lower payment than he is expected to pay back to the conventional generator at maturity. Panel (b) illustrates risk premia for the four example months, revealing that the wind power generator is selling his generation volume at a discount to the conventional generator in all example months. Based on correlation coefficients reported in Table 3.3, these results are expected, as the wind power generator's but-for-hedging profits are stronger correlated with the wind capacity factor than the conventional generator's, indicating that the risk reduction effect for the wind power generator is greater. Hence, he is willing to pay more than the conventional generator, which leads to the negative risk premium. Additionally, the equilibrium premia show a pronounced seasonality over the four example months. The wind power generator is willing to accept a discount for January roughly eight times greater than the discount he is willing to accept for July. This is again in line with the fact that the wind power generator has more value at stake in winters.



(a) (b)

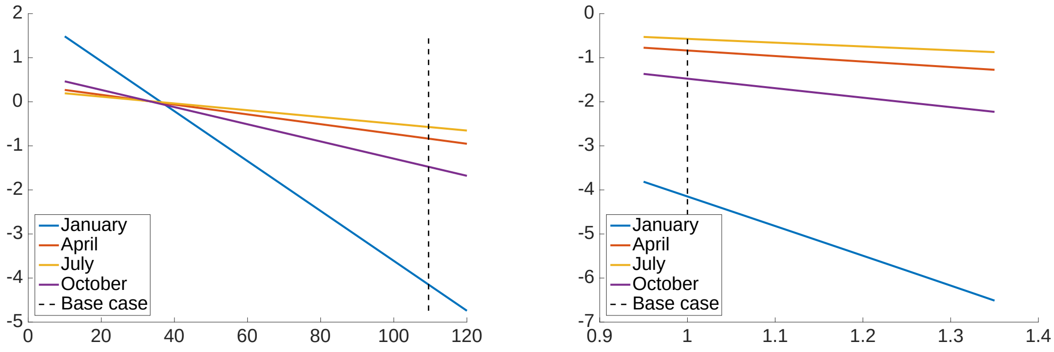
Figure 3.5: Risk premia on wind futures obtained from the equilibrium model for variations in the input parameters. (a) Premium sensitivity with regard to uniform changes in the both agents' risk parameters λ^W and λ^C (denoted as base-10 logarithms). (b) Premium sensitivity based on a variation of both parameters against each other. The x-axis is denoted in λ^W/λ^C.

Interestingly the traded equilibrium quantities are very similar across all four example months. They vary from 27 thousand in January and April to 28 thousand in July and October. The monetary market volume varies between 420 million EUR in January and 235 million EUR in July.

3.5.5 Sensitivity analysis for the agents' risk aversion

It is important to note that the two agents' risk aversion parameters only influence the absolute size not the sign of risk premia, as ξ is always positive for risk-averse agents. Figure 3.5, (a) shows that risk premia are highly sensitive to changes in risk parameter λ. The same result holds true when varying the two agents' risk parameters against each other as illustrated in Figure 3.5, (b). A smaller λ^W (relative to λ^C) leads to a smaller discount and a greater λ^W leads to a larger discount.

The risk premia approach zero, if one or both agent's risk aversion approaches zero, since if one of the agents approaches risk-neutrality his speculative position grows until the futures price is equal to its risk-neutral value – independent of his but-for-hedging



(a) (b)

Figure 3.6: Risk premia on wind futures obtained from the equilibrium model for variations in the wind power generator's profit function. (a) Premium sensitivity with regard to wind feed-in tariff P^W in EUR/MWh. (b) Premium sensitivity based on a variation of total wind capacity K in the system. The x-axis is denoted relative to actually installed capacity in 2015.

profits.

3.5.6 Sensitivity analysis for wind power generation profits

The wind power generator's but-for-hedging profits are expected to be mainly influenced by two factors in the future: decreasing wind compensation P^W and increasing wind capacity. Figure 3.6 illustrates that the two trends have an opposing effect on risk premia of wind futures.

Panel (a) shows that obtained discounts are highly sensitive to average wind compensation. The lower the tariff, the lower the discount. If the overall wind power profit decreases, the need to hedge and the supply for wind futures also decreases; increasing the futures price. The sensitivity is most pronounced for the January futures with the highest wind generation, and the lowest for July, when wind generation is smallest. The discount becomes a premium at an average compensation around 40 EUR/MWh, hence, way below its current and anticipated future levels. With a compensation lower than this threshold, conventional generators would pay an insurance premium to the wind power

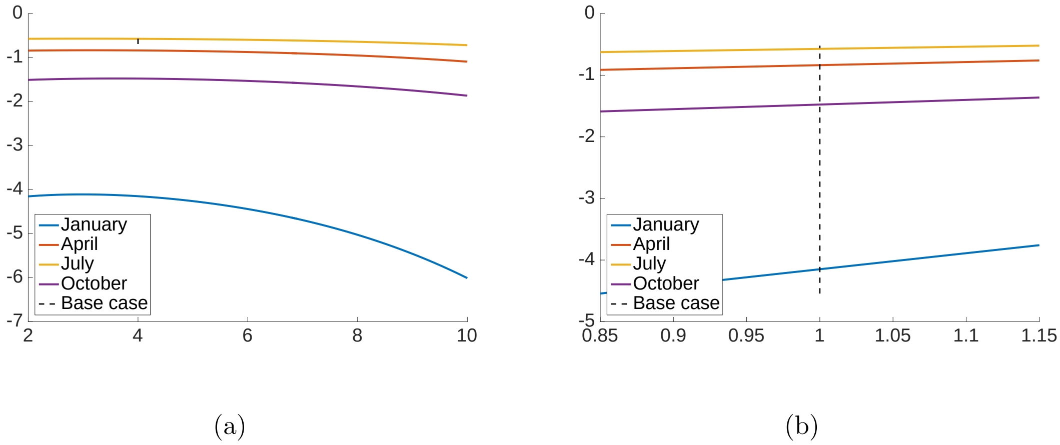


Figure 3.7: Risk premia on wind futures obtained from the equilibrium model for variations in the conventional generator's cost function. (a) Premium sensitivity with regard to the cost function's order o. (b) Premium sensitivity based on variation of overall power demand $\tilde{D}$. Its x-axis is denoted relative to actually simulated demand for 2015.

generators to lower their risk.

The effect of total wind capacity on risk premia can be analyzed under the assumption that there is no fundamental shift in wholesale price patterns due to the increase in wind capacity. This is only a reasonable assumption for incremental changes in wind capacity. Therefore, we limit the capacity growth in our sensitivity analysis to 10 GW or roughly 25%, which is the expected increase over the next four years, based on the objectives in Germany's *Renewable Energies Act*. Panel (b) of Figure 3.6 illustrates that the higher the total wind capacity in the system the larger the discount on the futures price. This is in line with the above analysis of the correlation of ρ with wind in-feed implying a higher hedging potential for wind power producers.

3.5.7 Sensitivity analysis for conventional generation profits

The conventional generator's but-for-hedging profits are mainly affected by two trends as well. First, the changes in the power markets may lead to changes in the shape (degree of convexity) of the supply function. Second, the overall power demand is potentially subject to change. It is affected by two developments: On the one hand, energy efficiency measures lower overall power demand. On the other hand, the partial electrification of the heat and mobility sector increases overall power demand. Figure 3.7 illustrates the effects of these changes on risk premia of wind futures.

Figure 3.7, (a) illustrates the premium's sensitivity with regard to the convexity of the system-wide cost function. The higher the function's order the higher are the discounts on wind futures, since a more convex cost function works like a buffer against wind volume risk for the conventional generator. High wind generation volume is generally disadvantageous for the conventional generator, but if its cost function is more convex, the effect is counteracted by disproportionally lower average generation costs. Hence, the conventional generator's but-for-hedging profits are the less correlated with the wind capacity factor, the higher the order of the cost function, which lowers the conventional generator's demand for wind futures, leading to higher discounts. However, the changes are limited close to our base case.

Figure 3.7, (b) displays the sensitivity of discounts with respect to changes in overall power demand. The greater the demand, the lower the discount. This is intuitive as overall demand is proportionate to the conventional generation volume and profit. The higher the conventional generator's profit, the higher also his willingness to pay for wind futures to hedge these profits. Note, that in the setup of this sensitivity analysis, an increase in overall demand does not affect the simulated power prices. An incorporation of this effect would supposedly amplify the sensitivity of risk premia to changes in demand, as higher demand leads to higher prices; resulting in higher conventional profits and again a higher willingness to pay for wind futures on the side of the conventional generator. For the reasonable range of changes in the conventional generator's but-for-hedging profits, the sign of risk premia do not change.

3.6 Conclusion

This paper presents an equilibrium model for the valuation of wind futures. It is based on the wind-related risk exposure of two central market participants that have a natural interest to take a position in these futures. Wind power generators are prone to take a short and conventional generators to take a long position to reduce their respective risks as is illustrated by our results.

To the best of our knowledge, this paper is the first that proposes an equilibrium model for the valuation of weather derivatives. Hence, the paper contributes to the understanding of pricing derivatives without a tradable underlying.

The equilibrium model builds on a comprehensive set of non-parametric models for random variables that determine the two agents' profit functions. The developed methods allows to estimate equilibrium futures prices, premia and traded quantities for wind futures. The central result that emerged from our investigation is that premia are expected to be negative, that is, wind power generators sell their expected wind generation at a discount to lower their risk. This result is stable for a very large range of changes in input assumptions – also when taking into account current trends such as renewable build-up and cost degression.

The discount acts as a potential source of compensation for conventional generators, who supply dispatchable generation capacity to the system, that is, a payment for providing system flexibility.

The absolute size of discounts is still unclear as market participant's risk aversion is unknown and could also be affected by speculators entering the market. These speculators could play an important role as long as the market is illiquid and the EEX asks large trading houses to assume the role of market makers.

Therefore, further research is required to test the developed equilibrium model once real futures prices are available: first, to estimate the risk parameters λ^W and λ^C; second, to empirically test the validity of the model.

A potential extension of the developed approach is to incorporate a full model of the conventional power plant park including its dispatch with intertemporal constraints and full cost coverage. This extension would have an effect on power prices and (marginal) costs. It would allow an in-depth analysis of the role of power plant flexibility for conventional generation profits and the resulting willingness to hedge.

To conclude, the analysis in this paper shows that wind as well as conventional power generators benefit from taking a position in wind power futures. This suggests that wind power futures may become a relevant asset class and help power generators to cope with weather-related uncertainties.

Chapter 4

On the Effect of Stochastic and Dynamic Residual Load Modeling in a Renewables-Based Power System

The technology mix in a renewables-based power system can be optimized by investment and dispatch models minimizing cost. These models' outcomes are strongly driven by their representation of residual load, which is the difference between power demand and renewable generation. Models usually either focus on a high temporal resolution or on a stochastic model. Available research suggests that both of these aspects make the model output substantially more accurate (e.g., Haller et al., 2012; Haydt et al., 2011), but their combination strongly increases computational requirements. Hence, I develop a parsimonious investment and dispatch model that allows to be based on residual load with high temporal resolution *and* a stochastic simulation. An application of the model to the German power system demonstrates the value of stochastic modeling. The same model with deterministic residual load underestimates the required wind and solar power, as well as storage capacities. Consequentially, it also underestimates the overall system costs.

4.1 Introduction

The decarbonization of our power generation has started in most regions around the world. It is part of the so-called 'energy transition' that has the objective to mitigate anthropogenic climate change. Two emission-free power generation technologies have emerged as the winners of the technology race: photovoltaic (PV) and wind power. They are widely expected to become the cheapest and by far the fastest growing power sources in the 2020s (Giannakopoulou and Henbest, 2016).

PV and wind power have three central characteristics differentiating them from conventional power sources: They are *intermittent, uncertain and decentral* (Hirth et al., 2015). As a consequence of these characteristics, PV and wind power cannot directly substitute conventional generation from coal- and gas-fired or nuclear power plants in a 'plug-and-play' fashion, but a transformation of the entire power system is required. The resulting 'renewables-based power system' is defined here as a power system in which the majority of power volume is generated from variable sources. Complementary technologies that might become widely used in this system are flexible conventional power plants, batteries, power-to-gas storage or demand response. The use of these complementary technologies creates *integration costs* additionally to PV and wind power's pure *generation costs*.

How the sum of *generation and integration costs* can be minimized is one of the most researched questions in the field of numerical model-based energy economics (Hirth, 2015). The focus on this question intensifies as PV and wind power's pure generation costs are becoming cost-competitive to conventional sources of generation. Hence, the central challenge is to integrate them into the overall power system. This aspect now determines the pace of the renewables build-out (Vahlenkamp et al., 2016).

The optimal technology mix in a renewables-based power system can be found by minimizing total system costs with *investment and dispatch optimization models* (Kondziella and Bruckner, 2016). Their outcomes are strongly driven by their representation of residual load, which is naturally always a simplification. Residual load models usually either focus on a *high temporal resolution* or on a *depiction of stochasticity*[1]. The first focus mainly covers PV and wind power's characteristic *intermittency*, while the second aspect covers its *uncertainty*. Available research suggests that both of these aspects make the model output substantially more accurate, but their combination strongly increases computational requirements (Haller et al., 2012; Haydt et al., 2011).

Models with a full temporal resolution of 8,760 h throughout the year typically assume perfect foresight and hence rely on a deterministic depiction of PV and wind power generation as well as demand patterns. But in reality the patterns are clearly stochastic and can vary strongly from one year to the next. Yearly wind capacity factors for instance varied between 14% and 22% from 2011 to 2014. Hence, picking a single historic base year for a model is likely to lead to significantly biased results. This hypothesis motivates my paper's *research question*:

What is the effect of stochastic and dynamic residual load modeling on the optimal technology mix in a renewables-based power system?

Thereby, the technology mix consists of PV and wind power capacities on the one hand, and of dispatchable system elements such as conventional power plants, load management and storage on the other. The answer also sheds light on the extensively researched question of what the cost-minimal technology mix is in general and what its sensitivities are regarding specific cost and technological developments. These aspects are naturally touched upon in this paper, but its focus remains on the benefit of stochastic versus deterministic dynamic modeling of residual load.

To this effect, I set up a *greenfield investment and dispatch optimization model* minimizing total system costs and incorporating an hourly scenario simulation of stochastic residual load. The model is specified for the German power system in a parsimonious fashion with regards to its techno-economic operational details, keeping it computation-

[1] See literature review in Section 4.2.2 for a detailed definition and comparison.

ally feasible. I generate two sets of optimized outputs: a first one based on a stochastic and a second one based on a deterministic dynamic representation of residual load.

This paper's main *contribution* is the comparison of these two sets of results, showing that the deterministic model underestimates the required PV and wind power, as well as necessary storage capacities substantially. Consequentially, the deterministic model also underestimates the overall system costs of the renewables-based power system. The error of the deterministic model increases with higher shares of variable generation. The combination of hourly temporal granularity *and* a full stochastic scenario simulation as well as its comparison to a deterministic representation is – to my knowledge – unique in this body of literature.

The second contribution of this paper is the formulation of an investment and dispatch model that is capable of incorporating an hourly resolution of stochastic residual load scenarios over an entire year. The optimization model itself is a two-stage linear programming model with the single objective of cost minimization and as such it is similar to existing work in this field. The similarity makes the results directly comparable to existing research results.

Third, this paper contributes to the literature on the optimal configuration of renewables-based power systems. It confirms pre-existing findings that a transition to variable generation sources is technically feasible, that storage is needed at a relatively late stage of 80% wind and share and that substantial curtailment of wind and PV power is economically optimal.

The detailed temporal and stochastic depiction of residual load patterns comes at the cost of an otherwise parsimonious model specification to keep computation feasible. One *limitation* of the model at hand is that it is based on a simplified depiction of the power system's techno-economic operational details. It includes one conventional generation, load management and storage technology respectively; all modeled in a stylized manner (see Sections 4.3 and 4.4.1 for details and discussion). These modeling choices are supported by a recent paper from Poncelet et al. (2016), who compared the gains in output quality between a more granular residual load representation and more techno-economic operational detail. Their results show that for high shares of variable renewables an improvement of residual load dynamics is clearly preferable.

Another limitation of the model is that it disregards elements of the renewables' characteristics uncertainty and decentrality. It omits renewables' short-term *uncertainty* by not including any balancing requirements, which are caused by a deviation between PV and wind power's short-term forecast and actual generation volume. While the model generally incorporates uncertainty with a set stochastic scenarios for residual load, these scenarios are entirely known to the decision maker. The reason for this modeling choice is that incorporating short-term balancing needs requires a separate simulation of wind and PV forecasts next to their actual generation, which would double the number of dispatch decision variables. Hence, omitting this aspect makes the problem substantially simpler, while the expected error is relatively small as future balancing costs are expected to be between 2–4 EUR/MWh (Hirth et al., 2015).

The model's limitation with regard to renewables' *decentrality* is that the power system is modeled as a single 'copper plate' without any grid restrictions. Moreover, the model does not include any imports and exports to neighboring network zones. A full optimization of more network nodes would require a full set of the model's decision variables for each node plus additional ones for the interconnector capacities. Hence, the model results do obviously not include an optimized network layout for our German example system. Nevertheless I consider the copper plate assumption as reasonable, because it is in line with the objective of the German government to keep one market zone and build out networks accordingly. Additionally, grid-related integration costs are expected to be smaller than the ones caused by intermittency. Evidence on grid-related integration costs is thin, but studies provide a consistent picture, which is that costs stay in the single-digit EUR/MWh range (Hirth et al., 2015).

4.2 Literature review

There exists an extensive body of literature on the optimal technology mix in a renewables-based power systems. A recent literature review by Allan et al. (2015) carves out that the optimal portfolio of technologies in fact needs to be a central scope of future research, as the economics of individual technologies are covered well.

Naturally there are several ways to classify and present existing literature and due to the vastness of the research area I devote Section 4.2.1 entirely to its segmentation. Thereby, I also locate this paper's research accordingly. In the following review of research results I mainly focus on methodological differences (Section 4.2.2). But in Section 4.2.3 I also give a brief overview of model outputs regarding the optimal technology mix.

4.2.1 Segmentation of investment and dispatch models

I choose three classification dimensions and discuss them in this section. First, Kondziella and Bruckner (2016) define *four perspectives from which the potential of individual technologies* in a power system configuration can be evaluated. Each perspective builds on top of the previous one.

1. Theoretical potential is the starting point and it describes all available physical energy content of a resource.

2. Technical potential takes technological and system constraints into account and describes how much of the theoretical potential can possibly be exploited through the use of technologies.

3. Economic potential additionally considers costs and benefits of competing individual technologies and represents an economic optimum.

4. Market potential furthermore incorporates the effects of (possibly imperfect) markets on a system's technology mix. It is equivalent to a market forecast.

Within these four categories, this paper's research question aims at the *economic potential* of different technologies. Hence, it incorporates technical constraints and individual technology costs as well as system interactions, but not the effects of market design.

Hirth et al. (2015) differentiate models, inter alia, based on whether they consider the overall share of *PV and wind generation in the system as an exogenous model input or an endogenous output* – our second classification dimension. An exogenous PV and wind share is usually sourced from policy objectives existent in Germany and many other countries. Hence, the model optimizes the system in order to match these objectives. In the endogenous case, there typically exists an externality assumption in the model – for instance a specific cost of carbon emissions.

In this paper the share of variable power generation is defined as *exogenous*. The respective literature stream, and therefore also this paper, is focused on the optimal capacity splits within the variable and the dispatchable group of technologies, but not between the two groups. Hence, this literature does not develop any direct recommendations on the reasonableness or pace of the energy transition, but on the evolving system configuration along a predefined pace of PV and wind generation build-out.

So my chosen approach is located in the research area, which aims to quantify economic potential of technologies based on an exogenous share of PV and wind power generation. Third, I classify the existing research in this area by the way it *represents the dynamics of residual load*, which is the most important source of uncertainty in the power system and it is the major driver of flexibility requirements and overall system configuration. Hence, a detailed understanding of different methodologies is highly relevant.

Methodologies can be classified with regards to three central aspects of residual load representation: *its spatial resolution, its temporal resolution and its depiction of uncertainty*. Spatial resolution is disregarded in the following literature review, in line with our model's underlying copper plate assumption (see discussion in Introduction). Hence, the following classification is based on the other two dimensions.

Temporal resolution of residual load can be captured in integral, semi-dynamic and fully dynamic form based on Haydt et al. (2011). In *integral* form, residual load is modeled by integrating slices of its duration curve. Dispatchable technologies are then optimized based on their mix of fixed and variable costs and required capacity factors. Integral form does not consider any real-time dynamics and is applied very rarely in current research. Hence, it is disregarded in the following. For *semi-dynamic* resolution, a set of typical days or hours of the year is selected for which the system is optimized. *Fully dynamic* models optimize the system for all 8,760 h of an example year.

Existing *uncertainty of residual load* may or may not be incorporated into the model, differentiating stochastic and deterministic models. *Stochastic* models are based on the entire distribution of residual load and *deterministic* models are based on one historic or expected realization of it.

Semi-dynamic models are in recent papers usually set up with a stochastic representation of residual load. Typical days for each season are selected in a way that they represent different realizations of PV and wind power feed-in. Hence, three categories of residual load representation are commonly used in current research: *stochastic semi-dynamic, deterministic fully dynamic and stochastic fully dynamic*. Selected research papers are referenced along these three categories.

4.2.2 Review on methodology: residual load dynamics

Stochastic semi-dynamic residual load

Stochastic semi-dynamic models focus on the stochastic representation of residual load, but choose a substantially less granular temporal resolution. Stochasticity is thereby incorporated by selecting a set of time slices that is representative of the entire distribution of potential realizations. Selection methodologies vary, but a separate stream of literature has evolved around the optimizing these selection procedures (Merrick, 2016; Nahmmacher et al., 2016). In return for their lower temporal resolution, models in this area often have a broader scope or finer resolution with regards to their geographic area.

Haller et al. (2012) present results from the LIMES model developed by the Potsdam Institute for Climate Impact Research. It covers Europe and the MENA region and includes endogenous transmission capacities. It is based on 49 characteristic time slices of 6 h each and the authors conclude that a higher temporal resolution needs to be the focus of future work. Bertsch et al. (2016) also publish a Europe-wide study using the model DIMENSION of the Institute of Energy Economics at the University of Cologne. The investment optimization is based on typical days for variable generation and power demand, but the applied selection procedure is not specified. The model covers 47 European sub-regions and the paper suggests that the main source of flexibility in 2050 is likely to be gas-fired generation; the only conventional generation technology included. The investment and dispatch optimization model E2M2s by Spiecker and Weber (2014) is based on 56 time slices made up of eight typical days (four yearly seasons with a week and a weekend day each) with seven typical hours each. They apply a recombining tree approach for PV and wind in-feed building scenarios for the 56 time slices. Their model includes 100 different conventional power plant classes, but no chemical storage such as lithium batteries for instance.

Some researchers have also explicitly analyzed the different model outcomes based on a stochastic and a deterministic semi-dynamic representation of residual load. Hart and

Jacobson (2011) compare a deterministic and a stochastic representation of renewable feed-in, power demand and outages on 28 typical days. They show that the deterministic approach overestimates carbon reduction potential by 33%. Storage is only considered in the form of solar thermal plants in their model and natural gas is the only fossil fuel based generation technology. Nagl et al. (2013) find that deterministic models have a bias towards greater RES capacity compared with dispatchable power generation (particularly for wind). They also underestimate total system costs. 2000 scenarios for 30 typical days are randomly picked in three-day blocks from two season intervals. From these 2000 scenarios, 10 representative ones are selected based on indicating values for PV and wind power generation at important sights. Hart and Jacobson (2011) and Nagl et al. (2013) show that a stochastic representation of residual load improves the accuracy of model results and is hence *preferable in comparison to a deterministic approach.*

Deterministic fully dynamic residual load

Deterministic fully dynamic models focus on a granular temporal resolution of residual load with all 8,760 h of the year, but disregard its stochastic nature. They are often applied in research focused on storage requirements and hence needing an accurate depiction of daily and yearly seasonality. They are also more common for greenfield models covering only one exemplary year and not the entire transition path.

A recent example of a greenfield model with a fully dynamic representation of residual load was published by Zerrahn and Schill (2015a). They present a greenfield investment and dispatch model with several sensitivity analyses and detailed representation of load management potential. The underlying residual load representation is deterministic, as 2013 is selected as the single base year for renewable generation and respective capacity factors. An integrated model for capacity planning and operational optimization based on a fully dynamic representation of residual load is also presented by Kuhn (2013). He simulates multiple scenarios for a fully dynamic representation of wind generation and finds strong differences from one year to the next. He then bases his analysis on a deterministic representation by picking the scenario closest to the expected yearly capacity factor. He thus incorporates a full temporal resolution, but only in a deterministic fashion.

Haydt et al. (2011) compare the benefit of such a full temporal resolution with a semi-dynamic approach. They find that semi-dynamic methods strongly overestimate the ability of renewables to fulfill demand and hence on the one hand underestimate the required PV and wind capacity as well as their costs and on the other hand overestimate their environmental benefits. Their semi-dynamic approach uses 288 typical time periods, while their fully dynamic approach is based on 8,760 h. They show that a full temporal resolution is *preferable in comparison to a semi-dynamic approach*. Other researchers have confirmed this finding on the value of a high temporal resolution (Ludig et al., 2011; Poncelet et al., 2016; Welsch et al., 2014).

Stochastic fully dynamic residual load

Stochastic fully dynamic models combine a granular temporal resolution and a stochastic representation of residual load. The research by Hart and Jacobson (2011) and Nagl et al. (2013) shows that a stochastic representation of residual leads to more accurate results, while the work by Haydt et al. (2011) indicates that a fully dynamic representation of residual load leads to more accurate results. But published research based on *stochastic and fully dynamic* residual load is very rare. The reason for this is computational feasibility as both dimensions drive the optimization problem's complexity.

One example of such an approach was published by Nicolosi et al. (2010). They compare stochastic fully dynamic to stochastic semi-dynamic representation by applying three different approaches with temporal resolutions of 8,760 h, 288 h and 16 time slices. Their simple stochastic representation consists of several historic generation years for PV and wind power and not on a full simulation. A case study for the ERCOT market in Texas illustrates that simplification of residual load dynamics by clustering has substantial effects on optimal capacity and dispatch results. They conclude that simplifying assumptions such as a semi-dynamic temporal resolution of residual load are not valid anymore in a renewables-based power system.

To my knowledge, there is no research on the comparison of stochastic vs. deterministic fully dynamic representations of residual load. This literature gap motivates this paper's research question.

4.2.3 Review on results: optimal system configuration

On a very general level, most of the presented literature agrees on a few central findings regarding the energy transition and the optimal configuration of a renewables-based power system; summarized as follows:

1. Transitioning the majority of power generation from conventional to variable sources such as PV and wind power is technically feasible, but it likely increases overall system costs (see, e.g., Henning and Palzer, 2015).

2. Storage is required only in the late stages of the energy transition process. Variable generation shares between 60% and 80% can be obtained by employing cheaper flexibility sources such as conventional generation and load management (see, e.g. Zerrahn and Schill, 2015b).

3. Curtailment of a part of surplus generation from PV and wind power is economically optimal, because negative residual load increases strongly in the late stages of the energy transition and it becomes very costly to build capacities, which could absorb the surplus (see, e.g., Schill, 2014).

But results on optimal variable and dispatchable capacities for the German power system vary in the details as Kirchner et al. (2016) illustrate in a meta-analysis of 25 recent studies from scientific and gray literature. The lack of coherence is moreover shown by Doetsch et al. (2014), who also publish a comprehensive meta-analysis and suggest that, particularly, results on required storage are not fully coherent because there is no consensus on appropriate models and correct scenario assumptions.

4.3 A parsimonious investment and dispatch model

I set up a greenfield investment and dispatch optimization model for the German power system. The model is kept parsimonious to enable a stochastic and fully dynamic representation of residual load and keep computation feasible. The formulation includes four technology categories: variable (variable and superscript V) and dispatchable (D) generation plants, storage (S) and demand response (L for load (management)). The number of individual technologies within each group remains undefined and unlimited in the general model, which is a two-stage stochastic optimization problem. First-stage decision variables are capacities K of individual technologies – the investment. Second-stage decision variables are the capacities' dispatch G throughout one example year with 8,760 h – the operation. Capacities K are always quantified in power (GW) and dispatch G is quantified in hourly power supply or consumption (GWh)[2].

To capture uncertainty in the example year, I base the optimization model on a simulation of stochastic demand as well as PV and wind power generation in N scenarios. Scenario-dependent variables are denoted by the subscript n. Details of the simulation approach are explained in Section 4.4.2. The dispatch optimization for a specific scenario is based on full knowledge of its realization throughout the year.

The model's objective is to maximize the power system's societal benefit, assuming the perspective of a social planner. The societal objectives for a power system are often summarized in the 'energy triangle' with its three competing dimensions: *efficiency, security of supply and sustainability* (CDU / CSU / SPD, 2013). I use these three dimensions to describe the model in detail and to validate that the chosen approach covers

[2] Storage level S represents the third group of decision variables and it is directly dependent on storage dispatch G^S.

all relevant aspects. Efficiency – the first dimension – is implemented as the objective function, while the other two are incorporated into the model as a set of constraints.

The power system's *efficiency* is maximized by minimizing its cost. To increase familiarity and comparability of results, costs are operationalized as expectation of system-wide levelized cost of electricity $LCOE_{System}$ in the example year.

$$\underset{K,G,S}{\text{minimize}} \quad E\Big[LCOE_{System}\Big] = E\left[\frac{C^V + C^D + C^S + C^L}{\sum_{t=1}^{T} \tilde{L}_t}\right] \tag{4.1}$$

$LCOE_{System}$ is calculated by dividing the sum of costs C^x in the four different technology categories x by the yearly sum of hourly power demand $\tilde{L}_t$. Different technologies in each of the four categories are denoted by the subscript j and C^x is the sum of their costs consisting of two components.

$$E\big[C^x\big] = \sum_{j=1}^{J_x} \left(K_j^x C_j^{x,fix} + \frac{1}{N} \sum_{n=1}^{N} \sum_{t=1}^{T} G_{j,t,n}^{x+} C_j^{x,var} \right) \quad \forall \quad x \subset \Big\{V, D, S, L\Big\} \tag{4.2}$$

First, there are annualized fixed costs $C_j^{x,fix}$ for each technology's capacity K_j^x. Second, there are variable costs $C_j^{x,var}$ for each unit of power supply $G_{j,t,n}^{x+}$ from technology j in hour t of scenario n. Expectation of costs C^x is calculated as the average cost over all N scenarios.

There are two stochastic components of the system model: demand $\tilde{L}$ and variable generation $\tilde{V}_j$[3] from J_I different PV and wind power technologies. Their difference is defined as the stochastic residual load $\tilde{R}$ in every hour t of each scenario n.

$$\tilde{R}_{t,n} = \tilde{L}_{t,n} - \sum_{j=1}^{J_I} \tilde{V}_{j,t,n} \tag{4.3}$$

The residual load has to be matched in every hour t of each scenario n through a dispatch of all available system technologies. The respective energy balance constraint ensures *security of supply* as the second goal dimension in the 'energy triangle'.

[3] Denoted as G^{V+} in Equation (4.2)

$$\tilde{R}_{t,n} = -G^{V-}_{t,n} + \sum_{j=1}^{J_D} \left(G^{D}_{j,t,n} \right) + \sum_{j=1}^{J_S} \left(G^{S+}_{j,t,n} - G^{S-}_{j,t,n} \right) + \sum_{j=1}^{J_L} \left(G^{L+}_{j,t,n} - G^{L-}_{j,t,n} \right) \quad \forall \quad t = 1, \ldots, T, \quad \forall \quad n = 1, \ldots, N \tag{4.4}$$

Dispatch decision variables are separated between positive and negative power supply, signified by G^{x+} and G^{x-}. In the case of storage and demand response both decision variables are necessary for calculation of variable costs and – in the case of storage – also to track storage level, as well as for various additional analyses of results. $G^{V-}_{j,t,n}$ represents negative power supply from overall curtailment of PV and wind generation.

So far no element in the optimization model supports the energy triangle's third goal dimension: *sustainability* of which I assume for our case that it is equivalent to a reduction in CO_2 emissions. The German government has the objective to achieve a reduction of CO_2 emissions in the power sector by continually replacing fossil fuel fired generation volume by generation from PV and wind power. These two technologies are widely seen as the winners of the technology race, offering low generation cost and a sufficiently high capacity potential in Germany (Bundesministerium für Wirtschaft und Energie, 2015).

Hence, sustainability is enforced in the model by an exogenous minimum share of PV and wind power generation – named ϕ^V. To analyze optimal greenfield system configurations throughout the transition, ϕ^V is increased over several optimization rounds. I do not link the minimum share to actual dates in the future, as the pace of transformation is politically determined and highly uncertain. To account for curtailment more simply, the constraint is formulated as the maximum share of demand provided from dispatchable generation $(1 - \phi^V)$ over all scenarios.

$$\sum_{t=1}^{T} G^{D}_{t,n} \leq (1 - \phi^V) \sum_{t=1}^{T} L_{t,n} \quad \forall \quad n = 1, \ldots, N \tag{4.5}$$

Besides the three competing goal dimensions of the energy triangle there additionally are several necessary technical bounds to ensure the feasibility of our results. First, all additional supply of power to the system has to be larger than zero and smaller than the supplying technology's installed capacity.

$$0 \leq G^{x+}_{j,t,n} \leq K^{x}_{j} \quad \forall \quad x \subset \Big\{V, D, S, L\Big\}, \quad \forall \quad t = 1, \ldots, T, \quad \forall \quad n = 1, \ldots, N \qquad (4.6)$$

Second, additional consumption of power by storage and load management also has to remain lower than installed power capacity.

$$0 \leq G^{x-}_{t,n} \leq K^{x} \quad \forall \quad x \subset \Big\{S, L\Big\}, \quad \forall \quad t = 1, \ldots, T, \quad \forall \quad n = 1, \ldots, N \qquad (4.7)$$

For simplification, I thereby assume that available load management capacity is only indirectly dependent on level of power demand[4]. Moreover, the reduction of available power through curtailment has to be lesser than all available variable generation in the respective hour t.

$$0 \leq G^{V-}_{t,n} \leq \sum_{j=1}^{J_I} \tilde{V}_{j,t,n} \quad \forall \quad t = 1, \ldots, T, \quad \forall \quad n = 1, \ldots, N \qquad (4.8)$$

Third, storage level $S_{j,t,n}$ is an additional decision variable. It needs to remain within the storage's installed energy capacity calculated by multiplying its power capacity K^{S}_{j} with its predefined energy-to-power ratio α_j.

$$0 \leq S_{j,t,n} \leq \alpha K^{S}_{j} \quad \forall \quad j = 1, \ldots, J_S, \quad \forall \quad t = 1, \ldots, T, \quad \forall \quad n = 1, \ldots, N \qquad (4.9)$$

The definition of storage level S incorporates the efficiency of the respective storage technology. Half of inefficiency is assumed to occur with input G^{S-} and the other half with output G^{S+}. The initial storage level $S_{j,0,n}$ is set to half of its energy capacity.

$$\begin{aligned} S_{j,t,n} = S_{j,t-1,n} + \frac{(1+\eta)}{2} G^{S-}_{j,t,n} - \frac{2}{(1+\eta)} G^{S+}_{j,t,n} \quad \forall \quad t \geq 1 \\ \text{with} \quad S_{j,0,n} = \frac{\alpha K^{S}_{j}}{2} \\ \forall \quad j = 1, \ldots, J_S, \quad \forall \quad t = 1, \ldots, T, \quad \forall \quad n = 1, \ldots, N \end{aligned} \qquad (4.10)$$

[4] The assumption is motivated by the fact that the range of hourly German power demand throughout the year is relatively small compared with renewable generation (Frontier Economics, 2014).

Fourth, the proposed model includes only the potential for load shifting, not for load curtailment, as curtailment's marginal costs are mostly too high to be relevant in our context. Therefore, all supply and consumption from load shifting have to even out every day (Frontier Economics, 2014).

$$\sum_{t=i-23}^{i} \left(G_{j,t,n}^{L+} + G_{j,t,n}^{L-} \right) = 0 \quad \forall \quad i = 24, 48, \ldots, T, \quad \forall \quad j = 1, \ldots, J_N, \quad \forall \quad n = 1, \ldots, N \tag{4.11}$$

Finally, the technical potential for PV and wind generation capacity as well as load shifting is limited in Germany.

$$K_j^x \leq K_j^{x,max} \quad \forall \quad x \subset \Big\{ V, L \Big\}, \quad \forall \quad j = 1, \ldots, J_x \tag{4.12}$$

The described optimization model is implemented in MATLAB and solved using the Gurobi solver through the YALMIP software package.

4.4 Data and assumptions for the German case

The proposed optimization model is applied to the German power system. It requires two groups of inputs: (1) assumptions for cost and technical parameters and (2) scenario simulations for stochastic residual load including power demand and variable generation. Details on both are given in the following two sections. The proposed general model is specified in a way that keeps the computational requirements to a minimum to allow for a representative number of scenarios and a set of sensitivity analyses.

4.4.1 Cost and technical input parameters

Assumptions for cost and technical model parameters are sourced from forecast studies, which include a detailed analysis of technological development potential. I define 2025 as the base year for all parameters, as it is the year when the German government expects to be roughly halfway through the energy transition (from 2000 to 2050). Either the selected studies provide a direct forecast for 2025 or the assumptions are interpolated from current data and forecasts for 2030 or 2050.

Please note that the model is specified as an isolated German power system. Obviously this does not fully match reality, where Germany is part of the evolving single European power market, which is a natural source of flexibility through geographic diversification of PV and wind power. Hence, the results presented here can be perceived as conservative estimates for future power system requirements.

The full set of base case assumptions and their sources are given in Table 4.1 and only some of them are commented on in the following sections.

Annualization of fixed costs for all technologies

The optimization model is built on variable and annualized fixed costs as the two direct cost inputs. Annualized fixed costs $C^{x,fix}$ for all technologies are calculated by annualizing CAPEX ($C_j^{x,exp}$) and summing them up with fixed yearly OPEX ($C_j^{x,fixOpex}$).

$$C^{x,fix} = C_j^{x,exp} \frac{i(1+i)^\tau}{(1+i)^\tau - 1} + C_j^{x,fixOpex} \quad \forall \quad x \subset \Big\{V, D, S, L\Big\} \tag{4.13}$$

Annualization of CAPEX also requires data for capital costs i and for the technologies' lifetimes τ. As a simplification, capital costs are assumed to be homogeneous across all technologies. They are sourced from a large survey for the European Commission among renewable energy investors resulting in 4% as the current average capital costs used as discount factor for German onshore wind investments (DiaCore, 2015). Lifetimes τ are sourced from the same sources as the respective cost parameters.

CAPEX are the biggest driver of annualized fixed costs for all technologies and they are also more familiar to most readers. Hence, to enhance transparency, Table 4.1 includes the underlying CAPEX assumptions. Additionally, sensitivity analyses are based on a variation of CAPEX, not on a variation of annualized fixed costs.

	Technical parameters				CAPEX for ... capacity		OPEX		Annualized fixed costs	Source
	Life	Eff.	Max cap.	E/P ratio	Power	Energy	Fixed p.a.	Variable		
	τ	η	K^{max}	α	$C^{exp,power}$	$C^{exp,energy}$	$C^{fixOpex}$	C^{var}	C^{fix}	
Technology	*years*	*%*	*GW*	*kWh/kW*	*EUR/kW*	*EUR/kWh*	*EUR/kW*	*EURcts/kWh*	*EUR/kW*	
Variable gen.										
Photovoltaic	27	24	300	–	830	–	17	0	68	Fraunhofer ISE (2015); Henning and Palzer (2015)
Wind Onshore	20	19	189	–	1,077	–	53	0	132	Henning and Palzer (2015); IRENA (2016)
Wind Offshore	20	13	45	–	3,145	–	62	0	293	Henning and Palzer (2015); IRENA (2016)
Gas-fired plants	30	61	–	–	1,019	–	31	5.1	90	International Energy Agency (2014)
Storage										
Batteries	11	91	–	1.9	98	375	10	0.1	103	Frontier Economics (2014); IWES et al. (2014)
Power-to-Gas	22.5	34	–	∞	1,850	0	10	0.1	136	Frontier Economics (2014); IWES et al. (2014)
Load mgmt.	25	100	7.7	–	835	–	0	0.1	53	Frontier Economics (2014); IWES et al. (2014)

Table 4.1: Base case assumptions for all available technologies. *Efficiency* mostly stands for energy conversion efficiency, but for variable generation technologies it represents the relative increase in capacity factors 2014–25, which can be applied directly to historic generation data 2011–14 for the different network zones. *Annualized fixed costs* are calculated from CAPEX, energy-to-power ratio, lifetime and fixed yearly OPEX, as well as the discount rate. Variable and annualized fixed costs factor directly into the optimization model.

Variable generation

The applied model includes $J^V = 9$ sources of variable generation: PV and wind power in each of the four German network zones respectively plus offshore wind generation in the North Sea.

In combination these nine sources have to supply a minimum share ϕ^V to the yearly power consumption. For the base case analysis, ϕ^V is varied in intervals from 20% to 80%. The starting level of 20% is the 2015 share of power consumption from PV and wind power. Please note that Germany's 2050 target is actually to generate 80% of its power from *renewable* sources including non-variable ones such as hydro and biomass. These non-variable renewable sources contributed a total of 13% to German power consumption in 2015, but their future growth potential is limited. Hence, PV and wind power need to contribute roughly 60-70% of German power consumption to reach the target of 80% renewables (AG Energiebilanzen e.V., 2015; Bundesministerium für Wirtschaft und Energie, 2015). I still consider a maximum share of 80% in this analysis and also base all sensitivity analyses on 80% variable generation to cover the transition process beyond the 2050 target.

Table 4.1 indicates that annualized fixed costs vary strongly between different variable generation technologies. In a rough description, they almost double from PV to wind onshore and double again to wind offshore. On the one hand these differences are mirrored by the technologies' expected full load hours per year, which are around 3–4 times higher for offshore wind than for PV. On the other hand Table 4.1 shows that PV is expected to have the highest efficiency increases, drawing the different technologies' output closer together. Variable costs are insignificant for all three energy sources, and are therefore, included in the stated fixed OPEX assumptions.

Table 4.1 also gives the technical maximum potential $K^{V,max}$ for German PV, wind on- and offshore capacity. Studies vary heavily in these limits. The assumptions chosen here are on the conservative side. The maximum potential for PV and wind onshore is distributed across the four network zones proportionally to installed capacity at the end of 2014.

Gas-fired power plants

Combined-cycle gas turbines (CCGTs) are defined as the only dispatchable generation technology ($J^D = 1$). This is a simplification that again helps to keep the model computationally feasible. Gas-fired power plants are chosen, because they are an effective complement to variable generation as they are highly flexible and have low CO_2 emissions (Bundesministerium für Wirtschaft und Energie, 2015).

Please note that CCGTs are modeled without any ramping or other inter-temporal constraints, which helps to keep the model parsimonious, but is also a simplification. Recent research supports this simplification by showing that conventional power plants have become increasingly flexible and that the effect of increasing variable generation shares on start-up costs is expected to be moderate (around 1% of variable generation cost) due to expected shifts in the power plant park to more CCGTs (Lambertz et al., 2012; Schill et al., 2016).

Nevertheless, due to this simplification the fully dynamic approach is not expected to yield a more realistic modeling of conventional power plants than a semi-dynamic approach. The value of the fully dynamic modeling is instead concentrated in the other technology groups, by incorporating the full seasonality of renewable generation and the dispatch of storage and load management.

Gas-fired power plants are the only technology in the modeled power system with variable costs of relevant size. They are calculated based on 2025 IEA forecasts for the natural gas price of 31.5 EUR/MWh and a CCGT efficiency of 61% (International Energy Agency, 2014). Disregarding costs for emission certificates, these assumptions yield variable costs for CCGT power generation $C^{D,var}$ of 5.1 EURcts/kWh.

Storage

CAPEX for power storage has two drivers: Its energy capacity defines the amount of power that can be stored and its power capacity defines the speed at which it can be charged or discharged. Both capacities have distinct cost assumptions that are transformed into one unique CAPEX assumption per power capacity based on a pre-defined energy-to-power ratio α:

$$C_j^{S,exp} = C_j^{S,exp,power} + \alpha_j C_j^{S,exp,energy} \tag{4.14}$$

Lithium batteries are included as the only storage technology ($J^D = 1$). This also helps to keep the model parsimonious, as every storage technology introduces a large number of inter-temporally dependent decision variables into the optimization problem. Power-to-gas would be an obvious choice for a second technology, because it provides longer-term energy storage – signified by its higher energy-to-power ratio α. But existing research has shown that long-term storage is not necessary or optimal for a variable generation share of 80% (see Section 4.2.3 or Zerrahn and Schill, 2015a). Running our model with both storage technologies and the assumptions given in Table 4.1 based on a low number of scenarios confirms this result. Central drivers for power-to-gas's lower attractiveness are its low efficiency and high power capacity CAPEX. These disadvantages are not compensated by its lower energy capacity CAPEX – even if they are assumed to be zero as in our case. Hence, power-to-gas is disregarded in the following analyses.

Load management

I specify load management as one aggregated technology ($J^L = 1$). It includes all load shifting potential available for an insignificantly small variable cost. According to a study by Frontier Economics (2014) for the German government, this includes mainly the potential in craft, commerce and services as well as in households. Total potential from these sectors is estimated to be around 7.7 GW in Germany (model constraint $K^{L,max}$).

4.4.2 Simulation of stochastic residual load

The work at hand is aimed at understanding the effect of a full simulation of stochastic residual load compared with using a single historic time series. Hence, all optimization results in this paper are reported for both residual load representations, while the applied optimization model is always the one presented in Section 4.3.

For the deterministic representation, the number of scenarios is reduced to $N = 1$. The stochastic representation includes a number of $N = 25$ simulated scenarios for the base case results and $N = 10$ simulated scenarios for the sensitivity analyses. Comparing results between these different numbers of scenarios reveals only small changes. Hence, I deem the smaller number of scenarios for the sensitivity analysis as acceptable.

Overall I include hourly time series for ten different system elements in the optimization model: German power demand; PV and onshore wind generation in each of the four German network zones and offshore wind generation in the North Sea. Power demand is included in GW and variable generation in hourly capacity factors. According to the model definition in Section 4.3, capacity factors are then multiplied by the decision variables K_j^V representing installed capacity in GW, resulting in variable generation in GW.

Historic time series for 2014 are used for the *deterministic representation*. Demand data are thereby sourced from ENTSO-E (2016). Capacity factors are calculated as ratio of two time series: Variable generation data are published by the network operators (50Hertz, 2015; Amprion, 2015; TenneT, 2015; TransnetBW, 2015) and PV and wind power capacity data are sourced from Deutsche Gesellschaft für Sonnenenergie (2015). Resulting capacity factors are scaled up with the forecasted efficiency gains until 2025 given in Table 4.1 to account for technological improvements in PV and wind power generation. I assume a constant yearly sum of power demand from today to 2025. Forecasts on power demand are highly controversial, because two trends counteract each other. Higher energy efficiency reduces demand, while electrification in the heat and mobility sector increases demand. Some studies expect a strong increase, others a strong decrease in power demand (Müller, 2015). Using a constant power demand from today to 2025 is obviously a simplification and it entails the implicit assumption that both trends balance each other out.

For *stochastic representation*, the dynamics of all ten time series are estimated and then simulated. Their dynamics are each modeled individually and then simulated in N scenarios with T hourly intervals. This granularity is necessary to capture distributional characteristics of residual load throughout the year, including yearly and daily seasonality. The applied stochastic models are identical to the fully non-parametric ones in Gersema and Wozabal (2016). Hence, they are only summarized briefly in this paper. Time series for PV and wind power's capacity factors as well as power demand are simulated with the same basic approach. The focus is thereby to not only provide a forecast for the random variables, but to capture their distributional properties over longer periods of time. Three steps are necessary to build these simulations.

1. The seasonal trend component is estimated using locally constant kernel regression. One seasonal trend times series is estimated for onshore wind power generation in each of the four network zones as well as for off-shore generation in the North Sea respectively. 24 distinct hourly time series are estimated for PV generation as well as power demand respectively to capture their daily seasonality.

2. Possible realization paths are simulated around the trend by blockwise bootstrapping from the in-sample trend model residuals. Random selection of these hourly residuals is done in blocks of one week to preserve serial correlation and from one of three yearly periods to account for yearly variations in errors.

3. The resulting simulation paths for wind and PV generation are then scaled up – like the historic time series – by the expected efficiency improvements given in Table 4.1.

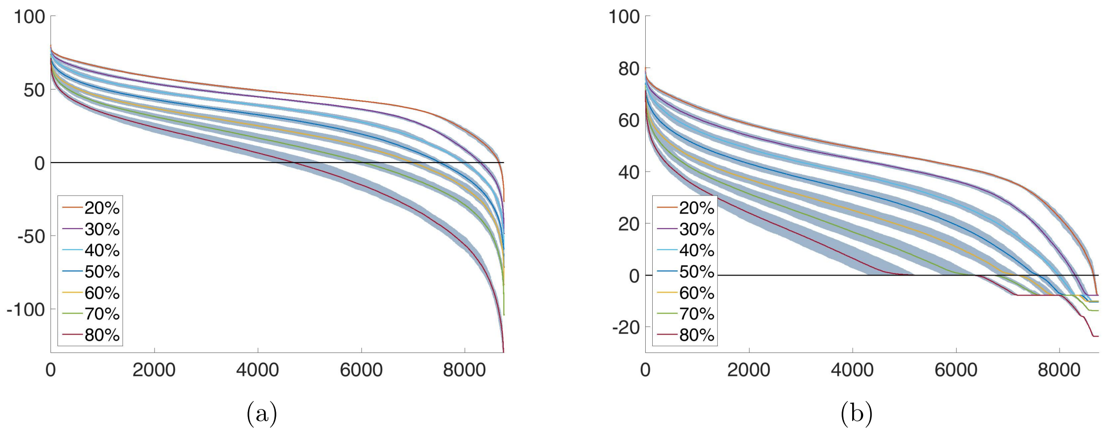


Figure 4.1: Hourly residual loads in GW (x-axis) over the example year – sorted from the hour with highest to the one with lowest residual load (y-axis). Lines represent the average residual load curve over all $N = 25$ scenarios. They are displayed in different colors for increasing shares of variable generation. The grey areas represent their 95% confidence intervals. (a) Residual load without any interventions in wind and PV generation or demand. (b) Residual load after optimal curtailment G^{V-}.

4.5 Results and discussion

Results are discussed in four steps. First, stochastic residual load – as central driver of future system operation – is analyzed. Second, I present base case results on optimal capacities along the energy transition process from the stochastic modeling approach. Third, these results are compared with the outcomes of the deterministic approach and the value of the stochastic solution is discussed. Finally, the results undergo an extensive sensitivity analysis by varying several input parameters.

4.5.1 Residual load analysis

All stochastic variables in the modeled system culminate in residual load. It needs to be matched by all dispatchable elements of the power system (here: gas-fired power plants, batteries and load shifting) during every hour of the year. Hence, residual load patterns drive optimal system configuration and require an in-depth analysis.

The following illustration of stochastic residual load patterns is based on optimal PV

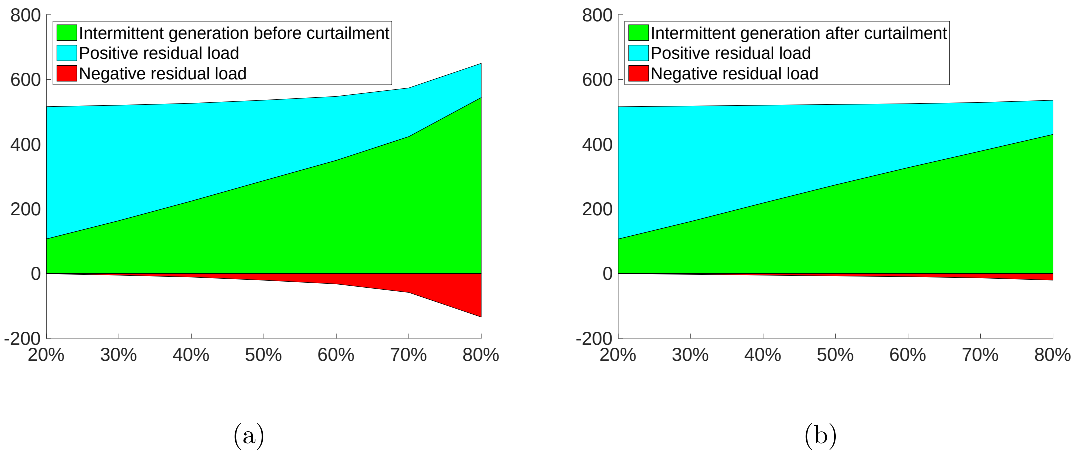


Figure 4.2: Yearly sum of wind and PV generation (in TWh), as well as positive and negative residual load (in TWh) for increasing shares of variable generation. The sum of these three components is equal to yearly power demand. The sum of positive and negative residual load is equal to the integral under and above the residual load curves in Figure 4.1. Results without curtailment [panel (a)] and after curtailment [panel (b)].

and wind power capacities K^V and optimal curtailment of their generated output G^{V-} from the specified optimization model.

Figure 4.1 displays how residual load patterns change with increasing shares of variable generation ϕ^V. It illustrates that there are five effects that I discuss in the following section: (1) negligibly smaller peak load, (2) steeper curve, (3) substantial overproduction, (4) existence and growth of yearly variations, as well as (5) the curtailment effect.

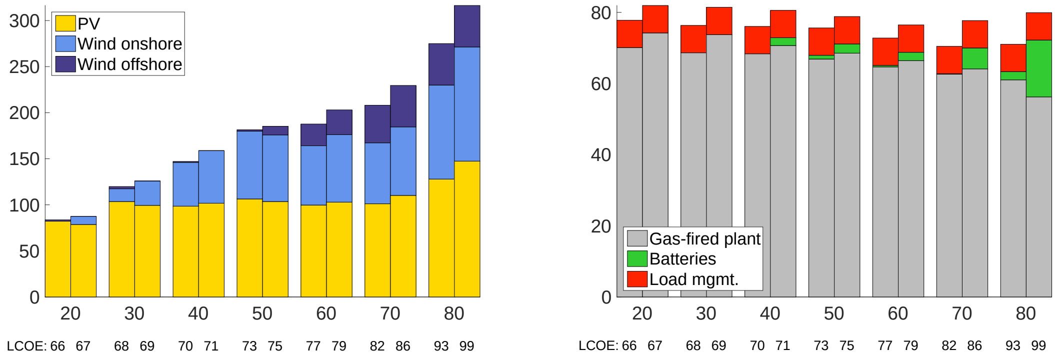
1. Yearly *residual peak load* decreases only slightly from 82 GW for 20 % variable generation to 75 GW for 80 %. There remain some hours during the year with a 'dark doldrums' situation, when there is almost no generation from PV and wind. During these hours the large majority of power demand needs to be satisfied from other power sources and their capacity needs to be held available throughout the entire year.

2. The middle section of the residual load curve (without the 500 most extreme hours on each end) becomes *steeper*. This means that there are less hours during the year

with similar residual load. From a conventional generation and system perspective, an optimal load curve was as flat as possible, because that allowed for steady and hence cost-minimal generation from nuclear and coal-fired power plants. The elements of the renewables-based power system need to adapt to a less steady generation pattern.

3. With 80% variable generation, there are on average 4,061 h or 46% of the year with *overproduction* from PV and wind power. During these hours there is not enough demand to consume the generated power volume – residual load is negative. This effect is illustrated in panel (a) of Figure 4.2, displaying the integrals under the residual load curves as well as variable generation volume. Together these components match yearly power demand. Expected negative residual load increases strongly from 0.8 TWh for 20% variability to 135 TWh or 26% of demand for 80%. The figure also illustrates the development of positive residual load, which naturally becomes smaller, when the share of PV and wind power generation increases. Its expected sum over the example year changes from 409 TWh for 20% variability to 106 TWh for 80%.

4. Additionally, there is a substantial amount of *variation in residual load curves* from year to year. The grey areas in Figure 4.1 indicate the 95% confidence interval. Their calculation is possible based on the underlying stochastic simulations. Their size shows that – even when disregarding the most extreme 5% of the years – the requirements put on the dispatchable elements of the power system vary from year to year. Confidence intervals also become wider with higher shares of PV and wind power. In the case of 80% variability, the yearly sum of residual load varies from 5 TWh to -59 TWh. The range of 64 TWh is equal to 12% of yearly demand. Hence, a selection of one possible scenario – in the form of one historic year – can underestimate the required system capacities substantially.



(a) (b)

Figure 4.3: Optimal capacities of different technologies (in GW on x-axis) for increasing shares of variable generation – starting from 20% to 80% of demand (y-axis). For each variable generation share there are two stacked bars. The left one results out of the deterministic, the right one out of the stochastic modeling approach (see Section 4.4.2). (a) Capacities of variable generation technologies. (b) Capacities of dispatchable technologies. Numbers in the bottom line are the $LCOE_{System}$ minimized by the optimization model.

5. Panel (b) in both figures illustrate the effect of *curtailment* G^{V-} as it results out of the optimization model. Curtailment reduces the range of hourly residual loads drastically – especially by capping off negative residual loads as panel (b) of Figure 4.1 illustrates. The average curtailment volume grows from 0.2% of PV and wind power generation in the 20% case to 21% in the 80% case. Figure 4.2 reveals that curtailment reduces the yearly volume of negative residual load by 85% in the case of 80% variability.

4.5.2 Optimal capacity mix – the base case

Optimal capacities for our set of base case assumptions are displayed in Figure 4.3. Results are reported separately for deterministic and stochastic modeling, as well as for variable and dispatchable technologies. In this section I will discuss general outcomes based on stochastic modeling to build a basis for the discussion of differences to the deterministic modeling approach following in Section 4.5.3.

As expected, panel (a) of Figure 4.3 illustrates that the sum of *solar and wind generation capacities* increases with their share of generated power. For the major part of the energy transition (up to 70% variability) their capacity increases at a disproportionately lower pace than their generation share. This is due to the fact that the increasing share of wind power (especially offshore) has a higher capacity factor than PV. For 80% generation share the required PV and wind power capacity jumps up. From this point on their generation occurs increasingly at times when demand is already fully satisfied (see Section 4.5.1 – especially Figure 4.2). Hence, not all output from additional capacity installations can be used and part of it is curtailed. Disproportionately more capacity is necessary to reach 80% variability.

PV is the cost-minimal technology of choice for the early stages of the energy transition with 20-30% of variable generation. In that phase it makes up more than 80% of PV plus wind capacity – based on our 2025 cost assumptions. PV reaches around 100 GW at 30% and then remains roughly stable until 70%. At that level of capacity it becomes less economic to install additional PV capacity as some of its generation volume has to be curtailed. Onshore wind power is built out steadily in the early phase and remains at 75 GW of capacity during the transition from 50% to 70% of variable generation. In that phase offshore wind power is gradually added until it reaches its maximum technical potential of 45 GW.

To reach 80% variable generation, additional PV and onshore wind capacities are necessary and they are also installed in some of the network zones with less favorable weather conditions, such as the Amprion zone. Overall the capacity split for the 80% stage is 147 GW PV (47% of variable generation capacity), 124 GW onshore wind (39%), and 45 GW offshore wind (14%); adding up to a total of 316 GW of variable generation capacity. The mix of PV (with more generation in summer) and wind power (with more generation in winter) apparently lowers the yearly residual load seasonality. A less seasonal pattern then allows for a cost minimal deployment of dispatchable technologies to balance out the variable ones.

The changes between capacities of different *dispatchable technologies* are moderate compared with the PV and wind build-out. Based on our cost assumptions, load management is used up to its maximum technical potential $K^{L,max} = 7.7\,\text{GW}$ from the beginning of the transition and for all stages going forward.

Other dispatchable capacity decreases only slightly in return for greater PV and wind capacity. It falls from 74 GW for 20% variable generation to 68 GW for 60%. The 6 GW reduction is entirely driven by the retirement of 8 GW gas-fired power plants, which are only partly replaced by 2 GW of battery storage. From 60% variability onwards, the dispatchable capacity increases again. While gas-fired power plants are continuously retired to a level of 56 GW for 80% variability, battery capacity increases disproportionately higher to 16 GW. Its power capacity is equivalent to an energy storage capacity of 30 GWh. Overall dispatchable capacity for 80% variability is at 80 GW, which is 2 GW higher than in the initial 20% stage.

During the transition period, *cost* in the form of $LCOE_{System}$ increases significantly from 67 to 99 EUR/MWh (48%). Thereby, the cost increase between the different transition stages accelerates. While one percentage point PV and wind power share leads to 0.18 EUR/MWh additional $LCOE_{System}$ between 20% and 30%, it increases by 0.69 and 1.32 EUR/MWh in the last two stage steps between 60% and 80%.

The reported $LCOE_{System}$ does also not fully illustrate the cost burden on the power consumer. It does not include any network (expansion) costs and the costs for renewable subsidies and networks are typically not split between end consumers proportionately to their power consumption – creating an even higher cost increase for household consumers.

Please note here that this analysis does not consider cost reductions during the transition as all stage results are based on the same greenfield model assumptions. Hence, it is misleading to set the stages equal to actual dates during the transition. The model simply uses the cheapest technology options first and moves on to more expensive ones once they are required to satisfy higher shares of demand from PV and wind power.

4.5.3 Stochastic vs. deterministic modeling

Capacity results based on a deterministic residual load representation differ in three central aspects from the stochastic modeling results.

1. Less renewable capacity throughout all stages
2. Fewer gas-fired power plants for all earlier stages $\leq 70\%$ variability
3. Lower storage requirements for all later stages $\geq 40\%$ variability

The deterministic model reports less PV and wind capacity for all stages of the transition. Panel (a) of Figure 4.3 additionally shows that the gap widens increasingly fast in the late stages of the energy transition. While capacity is 5 GW or 6% smaller for 20% variability, it widens to 41 GW or 13% for 80%. The reason for these differences is that the output of installed PV and wind capacity varies between scenarios as it also varies from one year to the next. The minimum share of variable generation ϕ^V has to be reached for all N scenarios. That is most likely less constraining for the generation pattern of one historic year ($N = 1$) than for a set of $N = 25$ scenarios.

Besides a lower total capacity, the deterministic approach also yields a different optimal split between the available technologies. Throughout the entire transition it yields lower wind generation capacities. For 20% variable generation, there are already 9 GW less onshore wind capacity and the gap increases to 22 GW for 80% or 18% less than from the stochastic model. The same effect results for offshore wind capacities during the late stages of the transition. Resulting PV capacities on the other hand are higher during the first phase of the transition, but also smaller during the later stages. For the final stage they are 19 GW or 13% lower.

Deterministic results also vary highly for required capacities in gas-fired generation and battery storage. In total there are 4–9 GW less dispatchable capacity than from the stochastic model. For all stages up to 70% variable generation, 1–5 GW or 2–7% less gas-fired power plants are required by the deterministic model. Up to that point the required battery capacities are relatively small for both models and do not differ substantially. But for 80% PV and wind power generation the deterministic model underestimates the required storage capacity massively. While its optimal battery power capacity remains around 2 GW, the stochastic model requires an additional 16 GW of batteries. With this configuration the model ensures the high share of solar and wind power generation for all $N = 25$ scenarios.

The differences between the modeling approaches also result in different expected system costs ($LCOE_{System}$). For most part of the transition – up to 70% variablity – they differ by modest 0.8–3.9 EUR/MWh or 1–4%. But cost results from the stochastic model jump at 80% – driven by the substantially higher PV, wind and storage capacity. At that point the deterministic model underestimates the system costs by 6.6 EUR/MWh or 7%.

Analyzing the *value of the stochastic solution* is helpful to substantiate the results. Hence, I compare the performance of the stochastic with the performance of the deterministic solution throughout our 25 scenarios. A first optimization run demonstrates that simply re-dispatching the deterministic solution throughout the stochastic scenarios – by re-optimizing all decision variables G^x and keeping original solutions for K^x – is infeasible. This finding is intuitively comprehensible, as the stochastic scenarios most likely cover a broader range of residual load realizations than the historic time series. So a classic analysis of stochastic value is not possible in our case.

Instead I additionally re-optimize the dispatchable capacity (K^D) and loosen the constraint on the maximum generation volume from gas-fired power plants. While several strategies are possible to approach the value of the stochastic solution, this one allows us to compare both solutions with regards to their sustainability impact, that is, their CO_2 emissions. Thereby, major parts of the optimization model remain identical to the original model presented in Section 4.3. Only the two following adaptations are necessary.

- Renewables (K^V), storage (K^S) and load management (K^L) capacities are no decision variables anymore. Instead they assume their values from the previous deterministic solution for a variable generation share of 80%.

- Constraint (4.5), which enforces the minimum share of PV and wind power generation volume ϕ^V, is taken out of the optimization model. Hence, more generation volume can be generated from gas power plants than only the remaining 20%. As this type of generation has the highest variable costs, our cost-minimizing objective function ensures that gas-fired generation is still at its minimum.

Moreover, allowing for more gas-fired generation would also be a realistic outcome in Germany, if the system was misconfigured based on our deterministic solution. The German regulator BNetzA currently forecasts the grid stability and considers all capacities projected to be installed. If there were doubts, they would contract existing fossil fuel fired plants as part of the capacity reserve, which would otherwise go offline.

The results of our re-optimization demonstrates that the updated deterministic solution is clearly less sustainable, but also cheaper than the stochastic solution. First, an additional 10 GW of gas power plants are added to the deterministic solution to enable a feasible dispatch that fulfills residual load in every hour of every scenario. This is an increase of 16%.

Second, the newly calibrated system misses the sustainability objectives of 80% renewable generation by a considerable margin. Over all scenarios only 78.6% of generation is renewable and in the worst case scenario it is only 74.5%. Consequently, the deterministic solution results on average in additional 3 Mt and in the worst case in 10 Mt of CO_2 equivalent emissions[5].

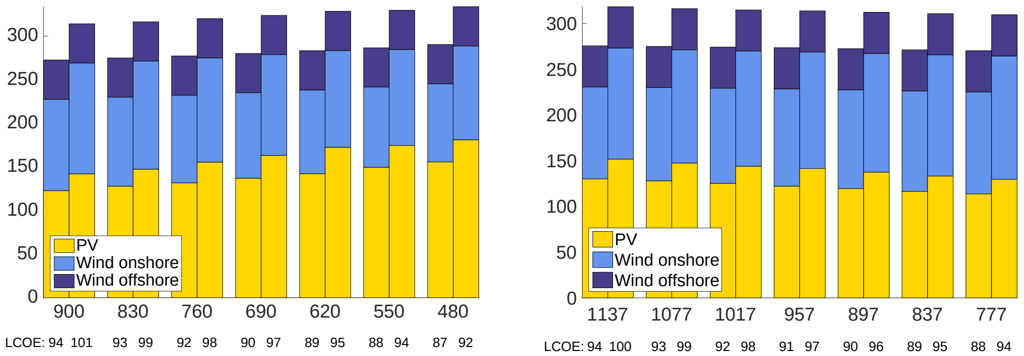
Third, and on the plus side, the updated deterministic solution is cheaper than the stochastic one. Its LCOE is 6.8 EUR/MWh lower. This is also intuitively comprehensible as gas-fired generation is cheaper than the combination of renewables plus storage. Overall the analysis of the value of the stochastic solution clearly substantiates and illustrates the benefits of stochastic residual load modeling.

To summarize, the comparison between both modeling approaches shows clearly that the deterministic approach underestimates the required PV, wind and storage capacities in the renewables-based power system. This also results in significant underestimation of system costs. The shortcomings of the deterministic model become more severe, the higher the share of variable generation. Running the deterministic solution's system configuration throughout our set of stochastic scenarios demonstrates that it is infeasible to ensure security of supply.

4.5.4 Sensitivity analyses on cost assumptions

A set of sensitivity analyses provides a robustness check of our base case results for an 80%. share of PV and wind power generation For each analysis I vary one central cost input parameter and analyze the effect on optimal capacities. Results suggest two central sensitivities or trade-offs: first, between the CAPEX of PV and onshore wind power, and second, between the CAPEX of gas-fired generation and battery storage. They are analyzed in the next two sections. The sensitivities of optimal capacities towards other cost input assumptions are described in the last section, but it shows that they are relatively small.

[5] Asssuming an emission factor of gas-fired generation of 369 t/GWh (Umweltbundesamt, 2016)



(a) (b)

Figure 4.4: Optimal PV and wind power capacities (in GW on x-axis) for changing CAPEX assumptions (y-axis). For each CAPEX input there are two stacked bars. The left one results out of the deterministic, the right one out of the stochastic modeling approach (see Section 4.4.2). (a) Effects of decreasing PV CAPEX from 900 EUR/kW to 480 EUR/kW. (b) Effects of decreasing wind power CAPEX from 1,137 EUR/kW to 777 EUR/kW. Numbers in the bottom line are the $LCOE_{System}$ minimized by the optimization model.

PV vs. wind power CAPEX

The results for optimal PV and wind capacities prove to be relatively robust – even for strong changes in their respective CAPEX assumptions. This sensitivity analysis is particularly important, because renewable CAPEX have proven to be very dynamic in the past. Especially the price of PV modules has decreased with a very high learning rate of 19-23% for each doubling of cumulative installations and the growth of installations was underestimated by nearly all forecasts (Fraunhofer ISE, 2015). Hence, there is a high degree of uncertainty around PV and wind power CAPEX assumptions – particularly a risk to underestimate CAPEX reductions. I focus on varying CAPEX of PV and onshore wind power, because offshore wind capacities already reach their maximum technical potential of $K_9^{V,max} = 45\,\text{GW}$ in the base case results for 80% variability.

CAPEX assumptions are varied in seven steps as illustrated in Figure 4.4 with a focus on reductions, not increases. The second bar from the left hence shows the base case results. The most extreme low cost assumption is more than 40% below the base case. The effect of these strong changes is surprisingly small. For the extreme low cost assumption of 480 EUR CAPEX per kW PV system (not just module), the optimal PV capacity is 23% or 34 GW higher and optimal wind capacity is 13% of 16 GW lower. The sensitivity is proportional to the cost reductions, which means there is not one particular threshold that causes a step change in optimal capacity.

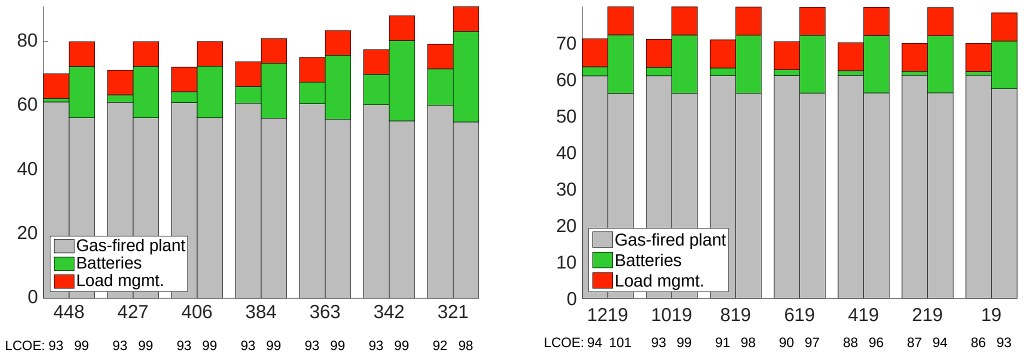
The effect of lower wind power CAPEX is similar, but naturally the changes in wind capacity are smaller than the ones in PV capacity due to PV's lower capacity factor. For a reduction of onshore wind CAPEX to 777 EUR/kW, optimal wind capacity is 9% or 11 GW higher and optimal PV capacity is 12% or 18 GW lower.

An important reason for the small sensitivity towards both cost reductions is likely the complementary nature of PV and wind power generation. Their generation at a specific time is negatively correlated. Hence, they cannot directly substitute each other if their relative costs change.

The effect of changes in PV CAPEX on optimal dispatchable capacities is entirely negligible. For the extreme reduction in wind CAPEX, 1 GW of battery storage is replaced by 1 GW of gas-fired generation. For PV the effect is exactly the other way around. Load management remains at its maximum technical potential in all cases. Total system costs naturally decrease with lower CAPEX. The effects are very similar for changes in PV and in wind CAPEX. In the most extreme cases the $LCOE_{System}$ is reduced by 6–7 EUR/MWh.

The relative differences between stochastic and deterministic modeling remain nearly identical. So the result that deterministic modeling substantially underestimates the required PV and wind power built-out is robust as well.

To conclude, the sensitivity analyses for PV and wind power CAPEX demonstrate the strong robustness of my results. For stochastic modeling the minimum PV capacity is 130 GW, the minimum onshore wind power capacity is 108 GW and the minimum offshore



(a) (b)

Figure 4.5: Optimal dispatchable capacities (in GW on x-axis) for changing CAPEX assumptions (y-axis). For each CAPEX input there are two stacked bars. The left one results out of the deterministic, the right one out of the stochastic modeling approach (see Section 4.4.2). (a) Effects of decreasing battery storage CAPEX from 448 EUR/kWh to 321 EUR/kWh energy capacity. (b) Effects of decreasing CAPEX of gas-fired power plants from 1,219 EUR/kW to 19 EUR/kW. Numbers in the bottom line are the $LCOE_{System}$ minimized by the optimization model.

wind power capacity is 45 GW. Current German capacities are all at least less than half of these minimum optimal capacities. Hence, it appears to be a 'no regret move' to expand capacities in all technology groups and decide on the 'fine-tuning' at a later stage.

Gas-fired power plant vs. battery storage CAPEX

Next to the insensitive optimal load management capacity, gas-fired power plants and batteries make up the dispatchable elements of the modeled power system. Batteries substitute relatively small shares of gas-fired generation capacity in the base case. Additionally, the substitution occurs for the most part in the late stages of the transition process. Hence, it is interesting to analyze how substitution is affected by CAPEX changes in these two technologies.

Battery CAPEX are changing very quickly at the moment. So far learning rates have proven suitable to model their cost development and for every doubling of cumulative production volumes costs have decreased by 6-9% (Nykvist and Nilsson, 2015). Increase of future production volume is highly uncertain, but other use cases than wholesale power market trading – such as electric vehicles and household storage – can potentially drive volumes up and hence costs down faster than anticipated in our assumptions.

I pick a range of assumptions for battery CAPEX comprising a reduction of 25%; from 427 EUR/kWh energy capacity to 321 EUR/kWh. Battery capacity increases substantially with lower CAPEX, but it barely substitutes any gas-fired power plants. The most extreme low cost assumption yields 12 GW or 77% more power capacity in batteries, but only 1 GW or 2% less in gas-fired power plants. This is equivalent to a 23 GWh increase in batteries' energy capacity. Interestingly the resulting reduction of system costs is almost negligible. In the most extreme case it is reduced by 0.9 EUR/MWh. The obvious reason for this is that additional battery storage only substitutes gas-fired generation disproportionately. Conventional power plants are still needed to cover the longer 'dark doldrums' periods. The deterministic approach generally yields a similar effect, but continues to substantially underestimate the optimal battery power capacity, while overestimating the optimal capacity in gas-fired power plants.

Our base case CAPEX for gas-fired power plants – or for conventional power generation more broadly – are also potentially inaccurate assumptions. For the base case model I consider full CAPEX for newly built power plants. But in fact there already exists more conventional power plant capacity in Germany today than our model's optimal results suggest necessary. Owners and operators of these plants do not base their operating and divestment decisions on full costs of newly built capacities, but on marginal costs of existing ones. Hence, I analyze the effect of massively lower CAPEX in conventional generation on the optimal capacity mix, accounting for the situation that a large share of conventional generation costs in existing German plants are sunk.

CAPEX for gas-fired power plants are varied from 1,219 EUR/kW to only 19 EUR/kW, which represents the hypothetical situation that all power plant CAPEX are fully sunk. In that case, gas-fired capacity is increased by 2% or 1 GW, while battery capacity is reduced by 18% or 3 GW. Reduced CAPEX of gas-fired power plants have a stronger effect on system costs than reduced battery CAPEX. For the most extreme case they are 6 EUR/MWh below the base case. Interestingly, the results of the deterministic approach are largely insensitive to these changes. In fact the output of deterministic approach grows more similar with low power plant CAPEX, because it yields lower storage capacity and higher gas-fired generation in the base case already. For low power plant CAPEX, the deterministic model even underestimates required capacity in both dispatchable technologies.

Optimal PV and wind power capacities are much less affected by both CAPEX changes. In the case of lower battery CAPEX, the required onshore wind capacity decreases by 10 GW, while PV capacity increases by 5 GW. The reason for this is PV's lower LCOE that can now – in combination with more battery capacity – replace wind power. In the case of lower gas-fired generation CAPEX, wind power capacity increases by 2 GW. Required PV capacity on the other hand remains largely unchanged. Offshore wind power is always built out to its maximum technical potential.

Based on the public debate in Germany on the future market design, the German government has passed the Electricity Market Act in 2016. It is supposed to assure that the cost-minimal combination of flexibility sources will be found as a market outcome. Based on the findings in this paper, it is advisable that the German government stays true to this plan. The presented sensitivity analyses suggest that several potential capacity combinations technically allow an 80% share of variable generation. Finding the exact future capacity combination through a cost competition between conventional generation and storage instead of regulatory predetermination is more likely to yield an efficient outcome.

Variations in other input parameters

Our model results indicate low levels of sensitivity for changes in other input parameters. Load management capacity is fully build out for all shares of variable generation in the base case. Hence, a reduction in its CAPEX does not yield an effect.

Changes in variable costs of gas-fired generation yield almost no changes in optimal capacities. In the case of higher generation costs up to 150 EUR/MWh, PV or wind power are not a direct substitute for gas power plants, because they would require storage to be available during the hours that are currently covered by gas-fired generation. In the case of lower variable costs, even if they approached 0 EUR/MWh, additional gas-fired generation would still break the minimum constraint of 80% variable generation. Hence, lower variable costs reduce system costs, but do not change optimal capacities.

4.6 Conclusion

An optimization of the future technology mix in the renewables-based power system, which is based on a deterministic representation of residual load, underestimates the required PV, wind power and storage capacities. This also results in a significant underestimation of system costs. The shortcomings of the deterministic modeling approach become more severe, the higher the share of variable generation.

Power demand and fuel prices used to be the predominant sources of a power system's uncertainty. With the transition to PV and wind power, uncertainty has increased and their variable generation has become its central source. But the depiction of PV and wind power generation in investment and dispatch models is still rather simple. They are either based on a low temporal resolution with a few typical days of the year or on a deterministic time series often in the form of one historic realization. The work at hand demonstrates the consequences of this second approach and should motivate to choose more sophisticated simulation approaches for residual load patterns.

This paper's detailed simulation of these patterns comes at the cost of an otherwise parsimonious model specification that includes only one conventional generation, storage and load management technology respectively. Future research could focus on developing and testing approaches, which combine the detailed simulation of variable generation patterns with a more sophisticated specification of dispatchable system elements.

In addition to analyzing the effects of stochastic vs. deterministic residual load, this paper also confirms some of the previous findings in this research area.

1. Optimal renewable power generation is split between PV and wind power to harness the benefits of their complementary nature with on- and offshore wind power combined having a somewhat higher capacity than PV.

2. Load management is a highly attractive source of flexibility, built out to its maximum potential under all sets of assumptions.

3. From a social planner's system perspective, storage becomes relevant at a late stage of the energy transition. PV and wind power generation patterns are spread out evenly enough over time to supply 70% of demand without being stored first. But to reach a share of 80% variable generation, some of the PV and wind generation needs to be stored and hence transferred to a period with unsatisfied demand.

Overall the results of this paper support an optimistic view on the feasibility of the energy transition. The technologies necessary to supply a large share of power demand from renewable sources are readily available. But for an efficient and well-planned transformation, an adequate depiction of fluctuating wind and solar power generation is necessary.

Chapter 5

Conclusion

5.1 Results and contribution

With my dissertation, I raise three novel questions around dealing with the *medium-term uncertainty* of wind and solar power. Uncertainty is one of three central characteristics of variable renewables and research on dealing with it has so far mostly been focused on either the long- or the short-term time horizon. While the long- and the short-term might have seemed more pressing for necessary investment and daily operating decisions, medium-term uncertainty induces substantial ongoing risks for several institutions in the energy sector. Hence, finding approaches to deal with it is highly relevant for the future roll-out of wind and solar power.

Institutions with a *microeconomic* perspective are, first and foremost, renewable energy investors with volatility in their cash flows. The first two essays present potential solutions for reducing their risks. But the examined approaches are also relevant for service providers in renewable energies, such as direct marketing providers. Moreover, financial institutions such as banks that provide funding for renewable projects and insurance companies that secure risks are directly faced with challenges from medium-term uncertainty. Lastly, conventional generators indirectly carry risks from medium-term uncertainty in renewable generation volume, which is negatively correlated to their own generation volume and power prices. All of these institutions are potential target groups for the research results in this dissertation's first two essays.

Essay I develops a portfolio optimization model for investors, who integrate their variable generation assets into a virtual power plant. Its application enables owners and operators of wind and solar power plants to substantially lower their portfolio risk as demonstrated with a case study for the German market. It is of particular importance to them to adjust their portfolio for the right mix between PV on the one hand and wind power on the other to reach an optimal risk/return profile.

An equilibrium pricing model for the newly introduced wind power futures is laid out in *Essay II*. It allows wind power investors to analyze the mechanics behind potential risk premia in futures prices. Based on a simulation we expect that these risk premia are always negative. Hence, the wind power generators are expected to pay an insurance premium to the conventional generators, while both are able to reduce their risk from fluctuating wind power volumes. The premium can also be interpreted as a compensation for the externality of a stable power system provided by the conventional generator.

Furthermore, my dissertation also addresses institutions with a *macroeconomic* perspective. Medium-term uncertainty in renewable generation makes system planning substantially more challenging, because it is uncertain for which conditions the system should be configured. To this end, *Essay III* assumes the perspective of a system planner and presents a parsimonious investment and dispatch model based on stochastic and dynamic residual load. The approach helps to create more realistic designs of the future renewables-based power system. In fact, a case study for the German system demonstrates that an alternative deterministic approach substantially underestimates the required PV and wind power capacity, as well as the required storage capacity. Consequentially, expected system costs are underestimated as well. A realistic representation of uncertain residual load is of such great importance, because a misconfigured system is either insecure, less sustainable than planned, or inefficient. All of these outcomes could impair the future prospects of the energy transition.

One overarching finding throughout my three essays is that the presented approaches to deal with medium-term uncertainty are currently not in use. The diversification and hedging approaches for investors, treated in the first two essays, show a lot of promise, but are only used to a very limited extent. Moreover, system planners do not consequently account for the medium-term uncertainty of residual load when optimizing the future power system design. Hence, I hope to contribute to a wider adoption of the presented approaches.

Additionally, to their individual contributions for dealing with uncertainty, all three papers demonstrate the relevance of *medium-term stochastic modeling* of variable power generation and other uncertainty drivers in the power system. To my knowledge, no directly comparable models have yet been published in peer-reviewed literature. Hence, the stochastic modeling approaches, developed in Essay I, are a contribution in their own right.

5.2 Outlook and questions for further research

All three essays show promise for further research in their area. The methodology in Essay I for risk-optimized pooling can be applied or adapted to include more technologies, more geographies, or more markets. Additional technologies could be combined heat and power plants, load management, or storage applications. Geographically the scope could be widened across Europe or even considering other continents to include more assets with very weak correlations among each other. A participation of the modeled virtual power plant in the balancing market could create value for dispatchable technologies in the portfolio, as they help to avoid balancing penalties from wind and solar power's uncertain generation.

Wind power futures, as analyzed in Essay II, are an entirely new field of research.

Hence, they offer a lot of potential to develop and test adequate pricing models once price data for wind power futures become available. Also, tests of the developed equilibrium model are still necessary to validate it. The first two essays both analyze approaches to reduce the investor's risk from variable power generation. Hence, a comparison of risk reduction benefits and costs for both approaches, including their potential combinations, shows promise for future research.

The results of my third essay naturally raise the question how a dynamic and stochastic representation of residual load can be incorporated in a less parsimonious investment and dispatch model. Potential enhancements could, foremost, include a more accurate depiction of dispatchable technologies' techno-economic operational details. Another objective could be to enlarge the set of included dispatchable technologies, with inclusion of long-term storage, such as power-to-gas, being an obvious choice.

All mentioned ideas for further research can help to deal with the medium-term uncertainty of PV and wind power and pave the way for them to become our primary energy sources. Their costs have already leveled with conventional generation in several regions around the world. During the time until 2040, their investment volume is projected to be twice as high as for fossil fuel fired and nuclear power generation combined (Giannakopoulou and Henbest, 2016). But the pace of the renewables build-out and thereby the pace of the energy transition will now be determined by our capability to deal with PV and wind power's unique characteristics. Hence, dealing effectively with their uncertainty, as an investor or as a system planner, is crucial for a successful mitigation of climate change.

Bibliography

50Hertz (2015). 50Hertz Grid Data.

AG Energiebilanzen e.V. (2015). Energieverbrauch in Deutschland im Jahr 2015.

Alexandridis, A. and Zapranis, A. (2013). Wind Derivatives: Modeling and Pricing. *Computational Economics*, 41(3):299–326.

Allan, G., Eromenko, I., Gilmartin, M., Kockar, I., and McGregor, P. (2015). The Economics of Distributed Energy Generation: A Literature Review. *Renewable and Sustainable Energy Reviews*, 42:543–556.

Allaz, B. (1992). Oligopoly, uncertainty and strategic forward transactions. *International Journal of Industrial Organization*, 10(2):297–308.

Allaz, B. and Vila, J.-L. (1993). Cournot Competition, Forward Markets and Efficiency. *Journal of Economic Theory*, 59(1):1–16.

Amprion (2015). Amprion Grid Data.

Artzner, P., Delbaen, F., Eber, J.-M., and Heath, D. (1999). Coherent Measures of Risk. *Mathematical Finance*, 9(3):203–228.

Bertsch, J., Growitsch, C., Lorenczik, S., and Nagl, S. (2016). Flexibility in Europe's Power Sector — An Additional Requirement or an Automatic Complement? *Energy Economics*, 53:118–131.

Bessembinder, H. and Lemmon, M. L. (2002). Equilibrium Pricing and Optimal Hedging in Electricity Forward Markets. *The Journal of Finance*, 57(3):1347–1382.

Bühler, W. and Müller-Merbach, J. (2007). Dynamic Equilibrium Valuation of Electricity Futures. *Working Paper, University of Mannheim.*

Bühler, W. and Müller-Merbach, J. (2009). Valuation of Electricity Futures: Reduced-Form vs. Dynamic Equilibrium Models. *Working Paper, University of Mannheim.*

Bundesministerium für Wirtschaft und Energie (2014). Gesetz für den Ausbau erneuerbarer Energien (Erneuerbare-Energien-Gesetz (EEG) 2014).

Bundesministerium für Wirtschaft und Energie (2015). Ein Strommarkt für die Energiewende (Weißbuch).

Bundesnetzagentur (2015). EEG in Zahlen.

Burger, M., Klar, B., Müller, A., and Schindlmayr, G. (2004). A Spot Market Model for Pricing Derivatives in Electricity Markets. *Quantitative Finance*, 4:109–122.

Bushnell, J. (2007). Oligopoly equilibria in electricity contract markets. *Journal of Regulatory Economics*, 32(3):225–245.

Bushnell, J., Mansur, E. T., and Saravia, C. (2008). Vertical Arrangements, Market Structure, and Competition: An Analysis of Restructured US Electricity Markets. *American Economic Review*, 98(1):237–266.

CDU / CSU / SPD (2013). Deutschlands Zukunft gestalten - Koalitionsvertrag zwischen CDU, CSU und SPD.

Chamberlain, C. (1983). A characterization of the distributions that imply mean-variance utility functions. *Journal of Economic Theory*, 29(1):185–201.

Conejo, A., Morales, L., Kazempour, S., and Siddiqui, A. (2016). *Investment in Electricity Generation and Transmission: Decision Making under Uncertainty*. Springer International Publishing.

De Giorgi, E. (2005). Reward-risk portfolio selection and stochastic dominance. *Journal of Banking & Finance*, 29(4):895–926.

D'Ecclesia, R. L. (2008). Risk management in commodity and financial markets. *Journal of Banking & Finance*, 32(10):1989–1990.

Deutsche Gesellschaft für Sonnenenergie (2015). EnergyMap.

DiaCore (2015). Web-based Database on Risk Profiles per Member State.

Doetsch, C., Grevé, A., and Rohrig, K. (2014). Metastudie Energiespeicher.

Draper, N. R. and Smith, H. (1998). *Applied Regression Analysis*. Wiley, 3rd edition.

Edwardes-Evans, H. (2015). German DM 'highly competitive'. *Platts - Power in Europe*, (695):1–2.

EEX (2016). Product Flyer for Wind Power Futures.

Ekren, B. Y. and Ekren, O. (2009). Simulation based size optimization of a PV/wind hybrid energy conversion system with battery storage under various load and auxiliary energy conditions. *Applied Energy*, 86(9):1387–1394.

Elton, E. J. and Gruber, M. J. (1997). Modern portfolio theory, 1950 to date. *Journal of Banking & Finance*, 21(11-12):1743–1759.

ENTSO-E (2016). Data Portal: Consumption.

Eydeland, A. and Geman, H. (1999). Pricing power derivatives. *Risk*, pages 71–74.

Eydeland, A. and Wolyniec, K. (2003). *Energy and Power Risk Management: New Developments in Modeling, Pricing, and Hedging*. Wiley, 1st edition.

Fabozzi, F. J., Kolm, P. N., Pachamanova, D., and Focardi, S. M. (2007). *Robust Portfolio Optimization and Management*. Wiley.

Fleten, S. E. and Lemming, J. (2003). Constructing Forward Price Curves in Electricity Markets. *Energy Economics*, 25(5):409–424.

Foley, A. M., Leahy, P. G., Marvuglia, A., and McKeogh, E. J. (2012). Current methods and advances in forecasting of wind power generation. *Renewable Energy*, 37(1):1–8.

Fraunhofer ISE (2015). Current and Future Cost of Photovoltaics - Long-term Scenarios for Market Development, System Prices and LCOE of Utility-Scale PV Systems.

Fraunhofer IWES (2015a). The European Power System in 2030: Flexibility Challenges and Integration Benefits.

Fraunhofer IWES (2015b). Wind Energy Report Germany 2014.

Frontier Economics (2014). Strommarkt in Deutschland – Gewährleistet das derzeitige Marktdesign Versorgungssicherheit?

Gersema, G. and Wozabal, D. (2016). Risk Optimal Pooling of Intermittent Renewable Energy Resources. *Available at SSRN*.

Giannakopoulou, E. and Henbest, S. (2016). New Energy Outlook 2016. *Bloomberg New Energy Finance*.

Golden, L. L., Wang, M., and Yang, C. (2007). Handling Weather Related Risks Through the Financial Markets. *The Journal of Risk and Insurance*, 74(2):319–346.

Graf, C. and Wozabal, D. (2013). Measuring competitiveness of the EPEX spot market for electricity. *Energy Policy*, 62(November):948–958.

Haller, M., Ludig, S., and Bauer, N. (2012). Decarbonization Scenarios for the EU and MENA Power System: Considering Spatial Distribution and Short Term Dynamics of Renewable Generation. *Energy Policy*, 47:282–290.

Handschin, E., Neise, F., Neumann, H., and Schultz, R. (2006). Optimal operation of dispersed generation under uncertainty using mathematical programming. *International Journal of Electrical Power & Energy Systems*, 28(9):618–626.

Hart, E. K. and Jacobson, M. Z. (2011). A Monte Carlo Approach to Generator Portfolio Planning and Carbon Emissions Assessments of Systems with Large Penetrations of Variable Renewables. *Renewable Energy*, 36:2278–2286.

Haydt, G., Leal, V., Pina, A., and Silva, C. A. (2011). The Relevance of the Energy Resource Dynamics in the Mid/Long-Term Energy Planning Models. *Renewable Energy*, 36(11):3068–3074.

Henning, H.-M. and Palzer, A. (2015). Was Kostet die Energiewende? Wege zur Transformation des Deutschen Energiesystems bis 2050.

Hirth, L. (2013). The market value of variable renewables. *Energy Economics*, 38:218–236.

Hirth, L. (2015). The Optimal Share of Variable Renewables: How the Variability of Wind and Solar Power Affects their Welfare-Optimal Deployment. *The Energy Journal*, 36(1):127–162.

Hirth, L., Ueckerdt, F., and Edenhofer, O. (2015). Integration Costs Revisited – An Economic Framework for Wind and Solar Variability. *Renewable Energy*, 74:925–939.

Huisman, R. and Kilic, M. (2012). Electricity Futures Prices Indirect Storability, Expectations, and Risk Premiums. *Energy Economics*, 34(4):892–898.

IEA (2014). Medium-Term Renewable Energy Market Report 2014.

Ilic, M. D., Black, J. W., and Prica, M. (2007). Distributed electric power systems of the future: Institutional and technological drivers for near-optimal performance. *Electric Power Systems Research*, 77(9):1160–1177.

International Energy Agency (2014). World Energy Outlook.

IRENA (2016). The Power To Change: Solar and Wind Cost Reduction Potential to 2025.

IWES, IAEW, and Stiftung Umweltrecht (2014). Roadmap Speicher - Speicherbedarf für Erneuerbare Energien - Speicheralternativen - Speicheranreiz - Überwindung Rechtlicher Hemmnisse.

Keles, D., Scelle, J., Paraschiv, F., and Fichtner, W. (2016). Extended forecast methods for day-ahead electricity spot prices applying artificial neural networks. *Applied Energy*, 162:218–230.

Kirchner, A., Koziel, S., Mayer, N., and Kunz, C. (2016). Metaanalyse: Flexibilität durch Kopplung von Strom, Wärme und Verkehr.

Kolos, S. P. and Ronn, E. I. (2008). Estimating the commodity market price of risk for energy prices. *Energy Economics*, 30(2):621–641.

Kondziella, H. and Bruckner, T. (2016). Flexibility Requirements of Renewable Energy Based Electricity Systems - A Review of Research Results and Methodologies. *Renewable and Sustainable Energy Reviews*, 53:10–22.

Köpke, R. (2015). Der Wettbewerbsdruck nimmt weiter zu. *Energie & Management*, 49(0):36–38.

Koppa, M. and Chovanec, P. (2008). A second-order stochastic dominance portfolio effciency measure. *Kybernetika*, 44(2):243–258.

KPMG (2015). Energy and Natural Resources, Taxes and Incentives for Renewable Energy.

Kuhn, P. (2013). *Iteratives Modell zur Optimierung von Speicherausbau und -betrieb in einem Stromsystem mit zunehmend fluktuierender Erzeugung.* PhD thesis, TU München.

Lambertz, J., Schiffer, H.-W., and Serdarusic, I. (2012). Flexibilität von Kohle- und Gaskraftwerken zum Ausgleich von Nachfrage- und Einspeiseschwankungen. *Energiewirtschaftliche Tagesfragen*, 62(7):16–20.

Longstaff, F. A. and Wang, A. W. (2004). Electricity Forward Prices: A High-Frequency Empirical Analysis. *Journal of Finance*, 59(4):1877–1900.

Ludig, S., Haller, M., Schmid, E., and Bauer, N. (2011). Fluctuating renewables in a long-term climate change mitigation strategy. *Energy*, 36(11):6674–6685.

Markowitz, H. (2014). Mean-variance approximations to expected utility. *European Journal of Operational Research*, 234(2):346–355.

Merrick, J. H. (2016). On representation of temporal variability in electricity capacity planning models. *Energy Economics*, 59:261–274.

Molderink, A., Bakker, V., Bosman, M. G. C., Hurink, J. L., and Smit, G. J. M. (2010). Management and Control of Domestic Smart Grid Technology. *IEEE Transactions on Smart Grid*, 1(2):109–119.

Müller, S. (2015). *Optimierung des Technologiemix in Deutschlands Energiesystem der Zukunft – eine methodische Auswertung deutscher Energieszenarien im Zeitraum von 2008 bis 2014.* Bachelor thesis, TU München.

Mulvey, J. M. and Erkan, H. G. (2006). Applying CVaR for decentralized risk management of financial companies. *Journal of Banking & Finance*, 30(2):627–644.

Nagl, S., Fürsch, M., and Lindenberger, D. (2013). The Costs of Electricity Systems with a High Share of Fluctuating Renewables: A Stochastic Investment and Dispatch Optimization Model for Europe. *Energy Journal*, 34(4):151–179.

Nahmmacher, P., Schmid, E., Hirth, L., and Knopf, B. (2016). Carpe diem: A novel approach to select representative days for long- term power system modeling. *Energy*, 112:430–442.

Nasdaq OMX (2015). Nasdaq OMX Contract Specifications of German Wind Index Futures.

Nicolosi, M., Mills, A., and Wiser, R. (2010). The Importance of High Temporal Resolution in Modeling Renewable Energy Penetration Scenarios. *Lawrence Berkeley National Laboratory Paper*, (4197).

Nykvist, B. and Nilsson, M. (2015). Rapidly Falling Costs of Battery Packs for Electric Vehicles. *Nature Climate Change*, 5(April):329—-332.

Pandžić, H., Kuzle, I., and Capuder, T. (2013). Virtual power plant mid-term dispatch optimization. *Applied Energy*, 101:134–141.

Perez-Gonzalez, F. and Yun, H. (2013). Risk Management and Firm Value: Evidence from Weather Derivatives. *The Journal of Finance*, 68(5):2143–2176.

Pilipović, D. (2007). *Energy Risk: Valuing and Managing Energy Derivatives*. McGraw Hill, 2nd edition.

Pirrong, C. and Jermakyan, M. (1999). *Valuing power and weather derivatives on a mesh using finite difference methods*. Risk Books, London.

Poncelet, K., Delarue, E., Six, D., Duerinck, J., and D'haeseleer, W. (2016). Impact of the level of temporal and operational detail in energy-system planning models. *Applied Energy*, 162:631–643.

Pudjianto, D., Ramsay, C., and Strbac, G. (2007). Virtual power plant and system integration of distributed energy resources. *IET Renewable Power Generation*, 1(1):10–16.

Redl, C. and Bunn, D. W. (2013). Determinants of the premium in forward contracts. *Journal of Regulatory Economics*, 43(1):90–111.

Reuters (2016). Europe's Exchanges Vie for Dominance of Wind Power Futures.

Rockafellar, R. and Uryasev, S. (2000). Optimization of Conditional Value at Risk. *Journal of Risk*, 2(3):21–41.

Rockafellar, R. T. and Uryasev, S. (2002). Conditional value-at-risk for general loss distributions. *Journal of Banking and Finance*, 26(7):1443–1471.

Schill, W. P. (2014). Residual load, renewable surplus generation and storage requirements in Germany. *Energy Policy*, 73:65–79.

Schill, W.-P., Pahle, M., and Gambardella, C. (2016). On Start-Up Costs of Thermal Power Plants in Markets with Increasing Shares of Fluctuating Renewables. *DIW Discussion Papers*, (1540).

Schwartz, E. S. (1997). The Stochastic Behavior of Commodity Prices: Implications for Valuation and Hedging. *The Journal of Finance*, 52:923–973.

Spiecker, S. and Weber, C. (2014). The Future of the European Electricity System and the Impact of Fluctuating Renewable Energy - A Scenario Analysis. *Energy Policy*, 65:185–197.

Szegö, G. P. (2002). No more VaR (this is not a typo). *Journal of Banking & Finance*, 26(7):1247–1251.

TenneT (2015). TenneT Grid Data.

TransnetBW (2015). TransnetBW Grid Data.

Tseng, C.-L. and Barz, G. (2002). Short-Term Generation Asset Valuation: A Real Options Approach. *Operations Research*, 50(2):297–310.

Umweltbundesamt (2016). Entwicklung der spezifischen Kohlendioxid -Emissionen des deutschen Strommix in den Jahren 1990 bis 2015. Technical report.

UN Environment Programme, Frankfurt School, and Bloomberg New Energy Finance (2016). Global Trends in Renewable Energy.

United Nations Framework Convention on Climate Change (2015). Paris Agreement.

Vahlenkamp, T., Ritzenhofen, I., Gersema, G., and Weber, M. (2016). Energiewende-Index Deutschland 2020 – Wie Deutschland seine Vorreiterrolle verteidigen kann. *Energiewirtschaftliche Tagesfragen*, 66(9):23–27.

Vasirani, M., Kota, R., Cavalcante, R. L., Ossowski, S., and Jennings, N. R. (2013). An Agent-Based Approach to Virtual Power Plants of Wind Power Generators and Electric Vehicles. *IEEE Transactions on Smart Grid*, 4(3):1314–1322.

Watts, C. (2011). Managing the Risk in Renewable Energy. *The Economist*.

Weekes, S. M., Tomlin, A. S., Vosper, S. B., Skea, A. K., Gallani, M. L., and Standen, J. J. (2015). Long-term wind resource assessment for small and medium-scale turbines using operational forecast data and measure-correlate-predict. *Renewable Energy*, 81:760–769.

Welsch, M., Deane, P., Howells, M., Ó Gallachóir, B., Rogan, F., Bazilian, M., and Rogner, H.-H. (2014). Incorporating flexibility requirements into long-term energy system models – A case study on high levels of renewable electricity penetration in Ireland. *Applied Energy*, 135:600–615.

Weron, R. (2008). Market price of risk implied by Asian-style electricity options and futures. *Energy Economics*, 30(3):1098–1115.

Zerrahn, A. and Schill, W.-P. (2015a). A Greenfield Model to Evaluate Long-Run Power Storage Requirements for High Shares of Renewables. *DIW Discussion Papers*, (1457).

Zerrahn, A. and Schill, W.-P. (2015b). On the Representation of Demand-Side Management in Power System Models. *Energy*, 84:840–845.