Numerical Frameworks for Challenges to the Transformation of Power Markets: Technology Choice, Cooperation, Model Capability

Inaugural-Dissertation
zur Erlangung des Grades
Doctor oeconomiae publicae (Dr. oec. publ.)
an der Volkswirtschaftlichen Fakultät
an der Ludwig-Maximilians-Universität München

vorgelegt von
Christoph Erich Weissbart

2019

Referentin: Prof. Dr. Karen Pittel

Korreferent: Prof. Brian Ó Gallachóir, Ph.D.

Datum der mündlichen Prüfung: 10. Juli 2019

Promotionsabschlussberatung: 24. Juli 2019

Acknowledgements

First of all, I thank my supervisor, Prof. Karen Pittel, for her constant support throughout the last five years. Her comments challenged me to emphasize the underlying intuition of my research and to think about real world implications. Furthermore, I thank her for giving me the opportunity to jointly establish a new field of research at the ifo Center for Energy, Climate, and Resources, which allowed me to work in a self-organized way, to get a glimpse of policy advice, and to establish my own network. I thank Prof. Brian Ó Gallachóir for our very valuable conversations at workshops and conferences and for being willing to serve as my second supervisor. Likewise, I thank Geoffrey J. Blanford for teaching me how to translate real world power markets into numerical models and for introducing me to the capability of numerical assessments. I also want to thank Prof. Georg Dürnecker for his immediate willingness to serve as my third examiner.

I thank my co-author Mathias Mier for our very efficient work and for sharing his knowledge of how to write academic articles. In the same way, I thank my co-authors Georgios Savvidis and Kais Siala for their professional attitude towards project work. I thank my colleagues from the ifo Center for Energy, Climate, and Resources for valuable discussions and for introducing me to fields of environmental and resource economics that I would not have encountered otherwise. Furthermore, I thank Oskar Achten, Christopher Kutz, and Julian Wichert for providing excellent research assistance at different stages of my dissertation.

The research conducted under Chapter 1 was funded by the Bavarian Ministry of Economic Affairs, Regional Development and Energy (StMWi). The German Federal Ministry for Economic Affairs and Energy (BMWi) supported the work on Chapters 2, 3, and 4 through the funded project "Research Network for the Development of New Methods in Energy System Modeling" (4NEMO).

Christoph Weissbart, March 2019

Contents

List of Figures

List of Tables

Preface

Managing and limiting the consequences of global warming is one of the greatest challenges of the 21st century.[1] There is scientific consensus that anthropogenic greenhouse gas (GHG) emissions are the chief cause of ongoing global warming (e.g., Cook et al., 2013, 2016). Thus, limiting future emissions at a level that allows for a moderate climate is crucial to preventing harsh consequences to humankind. The historic development of GHG emissions is mainly driven by the interplay between the growth of the economy and energy as well as emissions intensity.[2] The vast majority of these emissions stem from fuel combustion in, especially, power markets for providing firms and households with electricity.[3]

The specific characteristics of power markets render their transition towards a low emission intensity system difficult. This market builds on the utilization of a cost-intensive infrastructure (e.g., power plants and grid infrastructure), which requires long amortization periods. It is also subject to technical constraints, for example, to constantly balance demand and supply and to keep the grid frequency constant. An additional challenge to the long-run development of power markets is increasing demand. Apart from providing existing market participants with electricity that exhibits a low emission intensity, the supply side of power markets will have to provide new demand sectors with electricity. Other energy sectors, such as the transportation and heat sector, either exhibit high CO_2 abatement costs compared to the power market or their transition faces technical limitations (EC, 2016). Accordingly, the notion of a cost-efficient transformation of all energy sectors suggests the partial electrification of these sectors.

[1] Already now, the changing climate impacts economic activity and humans through, e.g., increased wildfire activity (Abatzoglou and Williams, 2016) and changing monsoon patterns (Herring et al., 2019).

[2] World annual CO_2 emissions evolved, throughout the different development steps of the world's economy, from 29 Mt in 1800 to 1,958 Mt in 1900 and were at a level of 36,179 Mt in 2015 (Boden et al., 2017).

[3] The combustion of gaseous, liquid, and solid fuels accounted for 93% of emissions from fuel combustion world-wide in 2013 (Boden et al., 2017).

The European Union (EU) is a prime example for the immense impact of fuel combustion for electricity generation on overall emissions. The share of electricity and heat production among the EU's total emissions from fuel combustion has increased steadily over the last 50 years.[4] Bearing that in mind, a fundamental yet smooth transformation of energy and electricity supply to a low emission intensity system, is necessary to limit GHG emissions and, thus, global warming.

Moreover, the character of the EU makes it of particular interest. First of all, the EU constitutes a political union between 28 member states. Member states are sovereign. However, the EU was given exclusive as well shared (with member states) competences such as the design of policies to combat climate change and to guarantee the secure supply of energy. Second, the EU was among the first developed regions engaging in international climate policy and signed the 1997 *Kyoto Protocol* for its first obligatory GHG reduction target. For the EU member states of that time, the Kyoto Protocol was translated into a mandatory reduction target of 8% until 2012 compared to 1990 levels. This was followed by mid- and long-term targets addressing the years 2020, 2030, and 2050. Finally, in response to the 2° C target of the 2015 *Paris Agreement*, the EU is currently revising its 2050 target to reaching a carbon emission-free economy.

These targets have to be translated into implications for all sectors of the economy and the power market in particular. Concerning the latter, it is crucial to understand the impact of EU climate policy goals on, among others, the costs for providing electricity, the mix of generation technologies, and the spatial distribution of electricity generation among member states. This helps to, for example, introduce required national and EU-wide legislation and initiate research and development efforts. Having that in mind, there is a great demand for quantitative assessments of the future development path of power markets and its sensitivity on numerous framework conditions (e.g., commodity prices). Models of power markets, which identify the long-run competitive equilibrium, are thus essential to analyze the implications of international and national climate and energy policies as well as other framework conditions on market outcomes.

Apart from analyzing general consequences on market outcomes, numerical assessments allow one to consider and quantify the various challenges to the transition of the European power market. Due to technical constraints, the set of substitutes for fossil fuel-based electricity generation technologies is limited with wind and solar power being regarded as the most promising group of technologies due to the past development and future prospects of their costs (IRENA, 2016). However, the intermittent supply pattern of

[4] The share of emissions from electricity and heat production in the European Union increased over the last 50 years from 31% in 1960 to 42% in 2014 (IEA, 2017a).

these renewable energy technologies, due to meteorological conditions, as well as their spatially varying resource quality is a great challenge to the constant and secure supply of electricity and hence their broad market integration. Consequently, complementary technologies, grid infrastructure, as well as conventional generation technologies will continue to play a crucial role, especially when renewable energies are not available to meet demand. In the same way, the demand side of the power market has to adjust to the ambitious decarbonization. An efficient use of electricity and the temporal reallocation of electricity demand are believed to be crucial to an efficient transformation path. Yet, electricity tariffs in the past have rarely reflected the temporal scarcity of resources and thus have not created incentives for the shifting of demand in time. Hence, new technologies on the demand side that allow for flexibility of electricity demand as well as new tariffs are required. Likewise, there are challenges from the design of the mandate of the EU. The EU sets the long-run climate and energy policy goals for all 28 member states. Yet, the translation of most of these goals into national legislation lies in the responsibility of member states, where the actual design of national legislation is, in addition to EU regulation, influenced by national interests. This shared responsibility between the EU and its member states imposes a political constraint on the translation of climate policies into actual targets or legislation. Another challenge is the interaction between current energy and climate policy questions and numerical assessments itself. The long-run transition of the power market results in various questions to policy makers and dealing with them requires quantitative assessments. Most questions are very specific and assessing them adequately requires a numerical model to capture the mechanisms that are of importance to a specific policy question. At the same time, one can observe single numerical models addressing a variety of questions. Having the technical limitations with respect to computational power and model tractability in mind, it may be questionable to what extent numerical assessment do always capture crucial mechanisms. Thus, it remains unclear whether the provision of adequate advice is a constraint itself.

This dissertation analyzes how the decarbonization goals impact the long-run development of power markets and evaluates its cost for the case of the European Union. It comprises four chapters with each analyzing a particular challenge to the transition of the European power market. In the following, I will sketch out the relevance and contribution of each chapter. This is followed by a separate, technical summary of all chapters with each building on a stand-alone article. Chapters 1, 3, and 4 are based on co-authored papers whereas Chapter 2 is single-authored.

The substitution of fossil fuel-based electricity generation by renewable energies is challenging due to the intermittency of the latter. This imposes a new role on both renewable energies, and the remaining supply stack which has to balance the intermittent supply of renewable energies. Consequently, finding the optimal mix of generation technologies that exhibits a low emission intensity and guarantees the secure supply of electricity is complex. In *Chapter 1* of this dissertation, I develop a framework for capturing the long-run dynamics of the supply side of power markets for the case of the European Union. The framework puts an emphasis on the detailed representation of the characteristics of intermittent renewable energies, which are derived from meteorological data, as well as includes a large set of other renewable energy and conventional generation technologies. I apply the model to an 80% CO_2 emission reduction scenario and derive a path of the optimal, long-run technology-mix.

In addition to major adjustments to the supply side, EU-wide decarbonization efforts build on the smooth coordination between the EU and its member states. All member states following a single, EU-wide CO_2 emissions reduction path leads to the cost-efficient realization of this path, but can result in varying costs of transformation among countries. Furthermore, the translation of climate policy goals into binding targets requires the action of each member state. If single countries are worse off with the market outcomes under the EU-wide transition path, they might announce their own energy and climate policy targets. Consequently, it is crucial to integrate and understand the consequences of national interests in power markets. *Chapter 2* of this dissertation applies the framework developed in Chapter 1 in a novel combination with concepts of cooperative game theory to look into incentives for cooperation among EU member states. My findings allow me to elaborate on the cost-efficient realization of a decarbonization path while accounting for national interests.

With respect to the demand side of power markets, the functioning of the firms as well as the prosperity of households and individuals is closely tied to the constant availability of electricity. However, the demand side also has potential for flexibility. Hence, short- and long-run demand adjustments are discussed as another important channel for mitigating the consequences from climate change. *Chapter 3* of this dissertation contributes a novel framework to depict the dynamic development of short-term demand response and energy efficiency improvements, which allows for an assessment of the partial equilibrium of power markets. I apply this framework to look into the role of long-run demand adjustment in the form of energy efficiency for the decarbonization of the European power market. The results reveal that renewable energies, nonetheless, remain the major channel for avoiding CO_2 emissions even under the presence of demand adjustment.

The technical and political challenges to decarbonization also increase the complexity of providing policy makers with adequate advice. Numerical analyses on the economic implications of energy policies in power markets have existed for a long time and have become of increased importance with the liberalization of power markets in Europe. The number of available models is vast, and respective numerical results exist in large numbers. However, from the perspective of policy makers and the scientific community itself, there is little knowledge concerning the overall capability of the existing population of models and to what extent they actually provide relevant and robust insights for policy makers and regulators. This serves as the starting point for *Chapter 4* of this dissertation, where I provide a framework for bridging the gap between model capabilities and demand from the policy side. The framework is used to provide a map of the characteristics of a set of power market models to current energy policy questions and to derive implications for the capability of numerical models for decision support.

Chapter 1 The first chapter stems from joint work with Geoffrey Blanford (Weissbart and Blanford, 2019). We develope a computable partial-equilibrium model of the European power market, the EU-REGEN model, that captures the main determinants for the supply-side adjustments in response to climate and energy policies. The model comprises a representative demand side, a perfectly competitive supply side, and a central planner and simulates a competitive, long-run market equilibrium over the horizon of 2015 to 2050. We focus in particular on the detailed depiction of renewable energy technologies, since the long-run development of power markets will be deeply affected by the gradual substitution of fossil fuel-based generation technologies by renewable energy technologies. However, the intermittent supply of renewable energy technologies, in combination with the temporal non-homogeneity of electricity, limits the competitiveness of renewable energies (Joskow, 2011). The model developed in this chapter contributes with a framework for capturing the temporal and spatial variability of wind and solar resources. Furthermore, we differentiate wind and solar technologies by different quality classes to account for the limited availability of high-quality resources. For that reason, we additionally contribute with a routine for using meteorological data to approximate the temporal availability of renewable energy technologies. The composite of all these renewable energy features allows then for a detailed representation of their market value and their implicit substitution elasticity with fossil fuel-based technologies. Our results for the long-run electricity generation path of the European power market show that, under an 80% CO_2 emissions reduction scenario until 2050, renewable energy technologies become the main technologies that will meet the demand. The 2050 generation-share of wind and solar power combined is around 40%. However, with the detailed depiction of their temporal and spatial characteristics, we identify that gas power is necessary as a complement to compensate for their intermittent supply. Furthermore, this requires in turn the utilization of carbon capture and storage to adhere to the climate target.

Chapter 2 In contrast to Chapter 1, this single-authored chapter, which is based on Weissbart (2019), goes beyond analyzing the first-best market outcome and is concerned with its stability. The cost-efficient market outcome builds on the notion of cooperation. In the context of power markets, this translates into regions that coordinate to maximize the overall welfare in the power market with respect to a climate target. Yet, it is well-known that the maximization of overall welfare through cooperation leads to redistribution and can result in the reduction of a region's welfare compared to the situation without cooperation. Thus, this chapter assesses why cooperation in the European power market might not be stable due to unequal cost-sharing and identifies cost allocations that account for national interests. I apply a two-part methodology in this chapter. First, I use the model developed in Chapter 1 to find the future equilibrium outcome of the European power market under a cooperative cost-sharing game. More specifically, I derive the first-best cost allocation for any possible coalition that can be formed among regions, which amounts in the setting of this chapter to $8,178$ coalitions. Second, I analyze resulting cost allocations by means of cooperative game theory concepts. Apart from combining a partial equilibrium power market model with concepts of cooperative game theory, this chapter develops the *carbon nucleolus* as a measure of the satisfaction of a coalition with a given cost distribution in relation to its emission reductions. The results show that the value of cooperation under a tight emission reduction target is a € 69 billion reduction in discounted system cost over the next 30 years, and rational behavior of regions can maintain at most 16% of this cost reduction. With the evaluation of alternative cost allocations, I identify a trade-off between accounting for robustness against cost changes and individual rationality. I also show that observed transfers within the European Union Emissions Trading System (EU ETS) are mainly in line with the results from this chapter. With respect to market outcomes, I find that the cost-efficient decarbonization path of the European power sector under the grand coalition is characterized by the interplay between wind power, gas power, and biomass with geologic storage of CO_2. However, with singleton coalitions only, the market outcome will shift to a higher contribution of nuclear power.

Chapter 3 The endogenous adjustment of demand is rarely considered in partial-equilibrium models of power markets. The third chapter, which is a joint work with Mathias Mier (Mier and Weissbart, 2018), explores the effect of responsive demand on the long-run market equilibrium of the European power market. In general, energy efficiency and short-term demand response are key issues in the decarbonization of power markets. However, their interaction and combined impact on market prices, as well as on the supply side, is yet to be understood. Thus, we contribute by developing a novel framework to implement investments in energy efficiency and short-term demand response in detailed partial equilibrium power market models. We then quantify our results by introducing this framework in the EU-REGEN model from Chapter 1 and find that, under an 80% emission reduction target, energy efficiency contributes only 11% of carbon emission reductions. Intermittent renewable energies such as wind and solar power account for the major share of 53% and fuel switching for 36%. Short-term demand response plays a crucial role by providing, instead of gas power, flexibility to deal with intermittency of renewable energies. Interestingly, we find that both energy efficiency and short-term demand response have their merits in reducing marginal abatement costs and additionally exhibit synergies on abatement costs, at least under an 80% climate policy. Our results recommend regulators to substantially promote the market penetration of smart devices and to establish economic incentives for adjusting demand to time-varying electricity prices.

Chapter 4 In the final chapter, which is joint work with Georgios Savvidis, Kais Siala, Lukas Schmidt, Frieder Borggrefe, Subhash Kumar, Karen Pittel, Reinhard Madlener, and Kai Hufendiek (Savvidis et al., 2019), this dissertation takes a step back from its numerical part and looks at the capability of numerical models to support decision-making. Apart from decarbonization targets, technology-specific policies and computational developments have led to increases in the complexity and diversity of so-called energy system models. Moreover, the lack of transparency and standardization has rendered the assessment of model suitability for specific policy questions difficult. This chapter contributes with a systematical assessment of the ability of energy system models to answer major energy policy questions. First, we examine the extant literature on model comparison schemes and then propose a set of criteria to compare a sample of 40 models. In the second part, a novel, model-oriented approach is developed to cluster energy policy questions. Finally, the model capabilities and the policy questions are brought together by quantifying the gap between models and policy questions. We find that some models are very well able to answer a wide range of energy policy questions, whereas others are only suitable for a specific area of energy policy. The representation of the distribution grid, the endogenous adjustment of demand, and the technical flexibility of the energy system are common features that deserve further research and development to address current energy policy issues. Our results provide policy makers with guidance on crucial model features with respect to a selection of energy policy questions, and suggest potential research directions for future numerical assessments.

Chapter 1

A Framework for Modeling the Dynamics of Power Markets – The EU-REGEN Model

1.1 Introduction

Since the beginning of the century, the energy policy of the European Union (EU) was mainly driven by the decarbonization of the supply side. The *power market* will be one of the main leverages to reach the ambitious decarbonization targets. On the one hand, electrification of other energy sectors and the conversion of power to other energy commodities (e.g., power-to-gas) will result in increasing demand (EC, 2011a, 2014). On the other hand, the electricity generation-mix has to reduce its CO_2 intensity. Therefore, renewable energy sources (RES) have to become the major source to meet this load. Their potential, especially for variable RES, is vast, and future cost estimates suggest economic viability (e.g., Coppens et al., 2009; Marcel Šúri et al., 2007; IRENA, 2016).[1] Yet, variable RES are spatially dispersed and their quality varies temporally. This means that a cost-efficient realization of EU decarbonization will require the integration of national power markets and EU-wide cooperation on climate and energy policy.

In 2008, the European Commission (EC) introduced the "Energy & Climate Package" with its "20-20-20" targets (EC, 2007). Comprising a 20% share of RES in energy consumption, a 20% reduction of greenhouse gas (GHG) emissions compared to 1990 levels, and a 20% reduction of final energy consumption compared to a business-as-usual scenario. Furthermore, each member state had to translate those EU-wide targets into national targets. To address the mid- and long-term perspective, the European Commission released "A roadmap for Moving to a Competitive Low Carbon Economy in 2050" (EC, 2011a,b), emphasizing a GHG emission reduction target of at least 80% compared to 1990 levels. In 2014, this decarbonization path was further specified by targets for 2030: a 27% share of RES in energy consumption, a 40% reduction of GHG emissions compared to 1990 levels, and a 27% decrease of final energy consumption. Currently, the EC updates its long-term target with now aiming for a carbon-free economy by 2050 (EC, 2018).

Existing models for the European power market already provide insight into the sector's future development under current RES and CO_2 emission targets. The LIMES-EU_+ model is used in Knopf et al. (2015) and Schmid and Knopf (2015) to look into the impact of the EC's RES generation targets for 2030 and the relationship between transmission capacity and RES capacity additions. Similarly, Schaber et al. (2012) analyze the impact of transmission capacity expansion for variable RES integration and quantify advantages and costs by means of the URBS-EU model. Kunz and Zerrahn (2016) apply the stochastic version of the ELMOD model to address the topic of congestion

[1] See, e.g., Huber and Weissbart (2015) for estimates on the variable RES potential in other regions of the world.

management between neighboring countries. Also the EMPIRE model considers uncertainty by stochastic optimization. In Brovold et al. (2014), the dispatch of hydro power is optimized under uncertainty with respect to meteorological circumstances. Moreover, the future role of nuclear power is examined in Aune et al. (2015). They use the LIBEMOD model to calculate the eoconomic costs of a phase-out of nuclear power by 2030. The economics of variable RES are further analyzed with the EMMA model in Hirth (2013) by emphasizing their market value. With a different focus, Deane et al. (2012) link results from the PRIMES energy system model (Mantzos and Capros, 1998) to the PLEXOS power system modeling tool (Energy Exemplar, 2018) to conduct a detailed evaluation of different power system components. A broader perspective is taken by Richter (2011) and Henning and Palzer (2014). The DIMENSION model focuses on the European power markets' interaction with the heat and transportation sector (Richter, 2011). A pure German perspective is taken in the REMod model to, however, examine the impact of different climate targets on endogenous sector coupling (Henning and Palzer, 2014). The behavior of private investors is researched in Schröder et al. (2013). They use the EMELIE-ESY model to optimize a long-run generation capacity investment under the assumption of profit maximizing agents.[2]

Yet, we still see analysis on the role of RES along the targeted decarbonization path that allow room for improvements. To provide insights into the role of variable RES technologies over time, further developments of their depiction in numerical models is required to analyze the relative costs of different technologies that rely on the same resource. Furthermore, the trade-off between utilizing regional resource qualities versus system-wide averaging effects of variable RES needs to be analyzed in dynamic models. Concerning conventional generation technologies, to elaborate on the future role of existing and new capacities in the European power market remains of great importance, and understanding their contribution in the coming transition phase is crucial to design relevant policies.

For that purpose, we developed the framework of the *EU-REGEN model*. The model was built to generate quantitative scenarios that represent an optimal and consistent decarbonization path for the European power system towards 2050. EU-REGEN minimizes total system costs with respect to conventional and RES generation capacity investment, generation capacity conversion and retirement, generation dispatch and curtailment, transmission capacity investment, physical electricity exchange, storage capacity investment and operation, and carbon capture and storage (CCS) capacity investment and operation. The model is set up as a partial equilibrium model that assumes complete

[2] See Chapter 4 and Connolly et al. (2010); Bhattacharyya and Timilsina (2010); Foley et al. (2010); Teufel et al. (2013) for a more extensive overview of existing power market models and their applications.

markets with perfect information and is subject to a wide range of constraints. Moreover, EU-REGEN is a deterministic and perfect foresight model. Meaning, there is no uncertainty about input parameters, for example, investment cost, fuel prices, and demand. The model is formulated as a linear optimization problem in GAMS (General Algebraic Modeling System) and solved with the CPLEX solver.

Among others, the optimization of investment into generation, storage, transmission, and CCS capacity is driven by costs for capacity additions and upper bounds on capacity additions and accumulation. Those bounds are derived from political and technical feasibility as well as geological and geographical potentials. Furthermore, electricity demand, which is determined exogenously in the model in this chapter, has to be satisfied by the combination of generation, storage discharge, and electricity exchange at any time. Dispatch of generation capacity and system operation are driven by marginal costs, availability, and investment costs of capacities. In addition, EU-REGEN makes use of the duality theorem and derives electricity and CO_2 prices from the dual variables of the market-clearing constraint and the system-wide CO_2 market constraint, respectively.

One specific characteristic of the EU-REGEN model is the detailed representation of the variable RES wind and solar. We apply different resource-quality classes to both resources, which are reflected in separate temporal availability profiles and capacity potentials for each quality class. Moreover, certain technological progress is assumed by setting improved technical characteristics of wind and solar technologies in future time periods.

This chapter provides an overview of the model set-up, the main assumptions, and a model application. We start with an introduction to the underlying economic rationale in Section 1.2. Then, Sections 1.3 and 1.4 present the model structure and resolution. This is followed by a detailed explanation of the methodology for modeling time-profiles for variable RES, the aggregation of time segments, and showing the major parameter values in Sections 1.5, 1.6, and 1.7. Finally, the model application to two policy scenarios with respective results is introduced in Section 1.8. Section 1.9 concludes with a brief outlook.

1.2 Model structure

In this section, we present the basic structure of the model and relate this to the microeconomic concepts underlying power markets. EU-REGEN is a partial equilibrium model of an electricity system consisting of multiple regions connected via transmission lines. It comprises consumers, producing firms, and a central planner (or regulator). This results in a multi-period investment and dispatch model. The model's main output variables are electricity prices, carbon prices, investment and production quantities of generation technologies, and investment in transmission capacities.

1.2.1 Demand side

Consumers demand electricity and obtain utility from this. We assume that the respective demand function $d(p)$ is downward-sloped, that is, electricity is a normal good whose demand decreases in its market price p. Meaning, the lower the price for electricity, the higher is the market demand. The inverse of the demand function $p(q)$, which indicates the price, that is, the willingness to pay, as a function of the available quantity q. The change in demand as a reaction to a change in the price is determined by price elasticity ϵ.[3] The absolute value of ϵ indicates the degree of demand adjustment. However, for the remainder of this chapter, we assume a price elasticity of $\epsilon \approx 0$ and thus demand is not reacting to price changes.[4]

1.2.2 Supply side

We assume a representative firm that invests in electricity generation capacity that is used to produce q quantities of electricity. Firms are assumed to be price-takers and hence their objective is profit maximization. Furthermore, the production of electricity is subject to technical constraints, which limit the feasible production set. This results in the supply function $s(p)$, which equals the market supply when there is only one representative producer, as in the case of the EU-REGEN model. The supply function is then a mapping of quantity q to the minimal costs for the provision of this quantity. Taking again the inverse of this function $p(q) = s(p)^{-1}$ results in the relationship between quantities and prices.

1.2.3 Central planner and social welfare

The central planner invests in transmission infrastructure between regions and maximizes social welfare. Social welfare in a market is defined as the sum of consumers' surplus CS and producers' surplus PS.[5] As shown in Figure 1.1a, the CS is characterized by the area between the demand curve and the horizontal line along the market-clearing price and can be interpreted as the overall willingness to pay that is not appropriated by the producers. The graphical representation of the PS is the area between the horizontal

[3] The price elasticity is defined as the percentage change in quantity over the percentage change in price. This can be written as $\epsilon = \frac{\Delta q/q}{\Delta p/p}$.

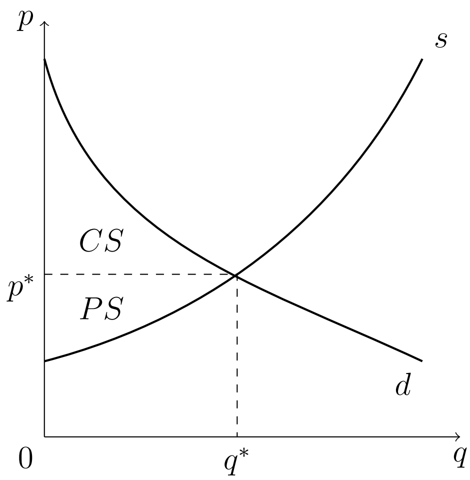
[4] See Chapter 3 for a model set-up with responsive demand.

[5] Note that the social welfare is also known as the Marshallian aggregate surplus.

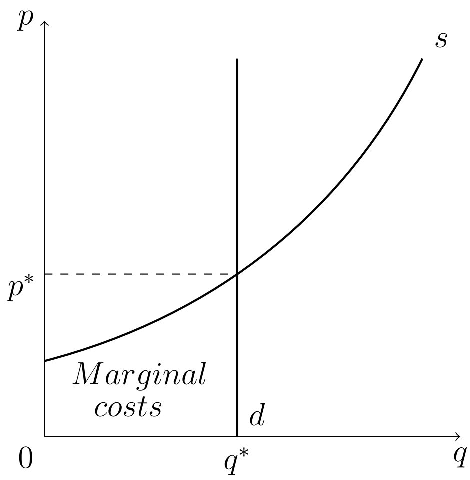
line along the market-clearing price and the supply curve. It can be interpreted as the overall revenue above the producers' costs or their profit. We assume that the assumptions of a competitive equilibrium hold and firms are price-takers, have access to perfect information, are not subject to any uncertainty, and hence obtain zero profit. It has been shown that the social welfare is maximized under the conditions of a competitive market and thus the efficient market equilibrium is reached.

As introduced above, we assume that demand is perfectly inelastic, that is, it does not react to changes in the market price. This market equilibrium setting is depicted in Figure 1.1b. Under this assumption, the maximization of social welfare does not distort the consumption choice of consumers. Thus, the minimization of total costs yields the social welfare maximizing market equilibrium, which is the area below the supply curve in Figure 1.1b.

We assumed, in this section, for illustration purposes, that producers incur only marginal costs for producing electricity. In the following, we will point out the economic rationale of the underlying market equilibrium and the type of costs that are considered in the EU-REGEN model.



(a) Elastic demand



(b) Perfectly inelastic demand

Figure 1.1: Market equilibrium under different demand elasticities

1.2.4 Market equilibrium

The long-run market equilibrium of the EU-REGEN model is based on the minimization of total system cost. The market value is the economic rationale underlying the solution to this problem (see Lamont, 2008; Borenstein, 2008; Hirth, 2013). This concept allows for a detailed depiction of RES, whose supply pattern is intermittent and exhibits a certain temporal correlation with demand.[6] This refers to the temporal non-homogeneity of electricity (Joskow, 2011).[7]

In brief, investment in capacity of a generation technology is cost-effective when its net market value is greater than the net market value of alternative generation technologies. The net market value is defined as the market value minus investment costs. Economic theory generally defines the market value mv, or marginal value, of a technology as the difference between the actual market price p^t and the variable costs of the technology VC. In the case of variable RES, the variable costs are close to zero. Hence, the annual market value of a generation technology is characterized by the sum over the differences between the market price and the variable costs multiplied by the hourly availability factor AV^t. For variable RES, the hourly availability factor AV^t represents the observed availability profile. In terms of generation technologies that are dispatchable,[8] this availability factor is assumed to be equal to 1 and can be dropped. Hence, the market value equals the weighted mean of the market price p^t that is corrected for the variable costs VC. This can be expressed with the time-weighted arithmetic mean of the marginal price:

$$mv = \sum_t ((price^t - VC) \cdot AV^t) = A((price^t - VC) \cdot AV^t) \cdot T. \tag{1.1}$$

Focusing on variable RES and thus neglecting the variable costs and keeping the availability factor, the capability to meet demand is another perspective on the market value. This means that a generation technology's long-term value is high when its availability profile allows for serving the market in times of high prices. In the analogy of Lamont (2008), the covariance can be used to divide the market value into two components. The covariance between the price and the hourly availability factor AF^t can be expressed as:

$$cov_{p,AV} = A(p^t \cdot AF^t) - A(p^t) \cdot A(AF^t). \tag{1.2}$$

Rearranging Equation (1.2) and substituting $cov_{p,AF} + A(p) \cdot A(AF^t)$ into (1.1) brings us to the following definition of the market value:

$$mv = A(p^t) \cdot A(AF^t) \cdot T + cov_{p,AV} \cdot T. \tag{1.3}$$

[6] A technology is intermittent when the temporal output variation is driven by exogenous factors.

[7] Note that the economic viability of different generation technologies can also be evaluated with a lower degree of detail, e.g., levelized costs of electricity generation (LCOE) (Kost et al., 2013) or average cost functions (Stoft, 2002).

[8] A technology is dispatchable when there is temporal control over it.

Equation (1.3) contains both components of the market value. The first term is the energy value and the second part is the demand-matching capability. The energy value indicates that, in this case, the market value of an intermittent generation technology depends, on the one hand, on the amount of energy that can be provided by adding one unit of capacity. On the other hand, the demand-matching capability comprises the value of serving the market in times of high prices and hence contributes to a reduction in this price with the low marginal costs of variable RES.

Correcting the market value for the fixed costs FC and investment costs IC yields the net market value nmv by:

$$nmv = mv - IC - FC = A(p^t) \cdot A(AF^t) \cdot T + cov_{p,AF} \cdot T - IC - FC. \tag{1.4}$$

With respect to the market equilibrium of the EU-REGEN model, this means that the optimal investment decision in each time period is determined in the order of the net market value of technologies and by the set of constraints that defines the feasible production set. Moreover, it is important to emphasize that market value is a dynamic concept. The investment decision of previous periods impacts market prices in a period and hence the market value of technologies.

1.2.5 Elements of system costs

As mentioned above, total costs in a market serve as a measure for global welfare under the assumption of perfectly inelastic demand. With respect to power markets, these costs are referred to as total system costs. They comprise the costs for providing electricity to the market as well as the investment costs for the underlying generation and transmission infrastructure. Moreover, costs can be differentiated between private and social costs.

Private costs The EU-REGEN model covers all costs that a representative firm incurs for generating electricity. However, the composition of private costs for producing electricity varies with the type of generation technology.[9] In general, we can differentiate technologies along two dimensions: RES-based/fossil fuel-based technologies and intermittent/dispatchable technologies. Costs occurring with the production of electricity can be differentiated into investment cost, variable cost, and fixed cost.[10]

[9] Private costs are understood as all costs that firms take into account when maximizing their profits.

[10] Note that investment costs occur only once to create one additional unit of electricity generation capacity, whereas fixed costs arise in each time period where a respective unit of capacity is active.

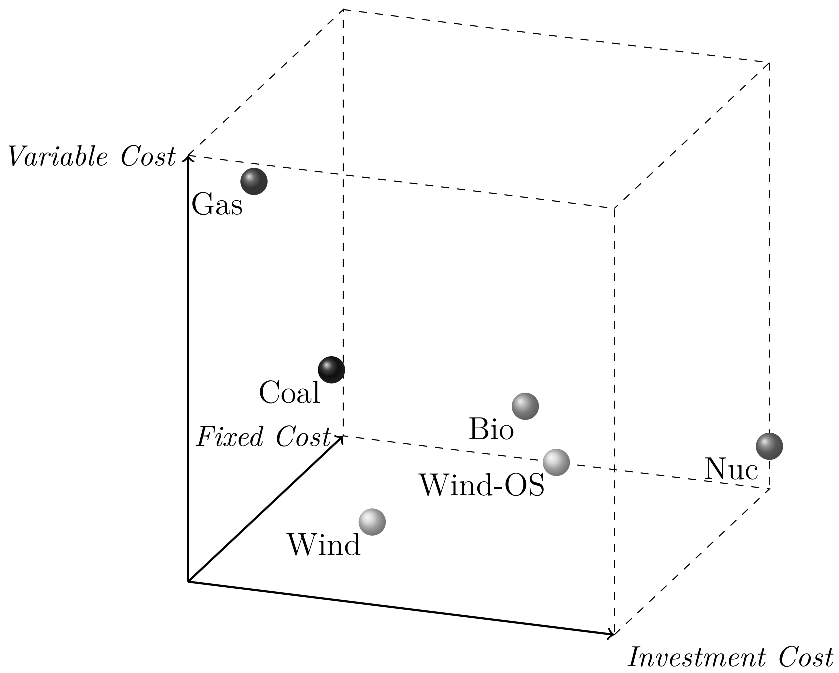


Figure 1.2: Magnitude of cost types by generation technology

Yet, different generation technologies cause each of these costs to a varying extent. Whereas dispatchable technologies are subject to all three kinds of costs, intermittent generation technologies induce negligible variable cost. Figure 1.2 indicates the relevance of investment, variable, and fixed costs for major generation technologies. This is done by locating each technology in the space of investment costs, variable costs, and fixed costs. We look at the standard generation technologies: biomass, coal, gas, nuclear, and wind. The magnitude of each cost component is based on Schröder et al. (2013).

Electricity generation from biomass is subject to relatively high investment cost and moderate variable and fixed cost. The latter is comparably high for nuclear power, which also triggers very high investment cost and moderate variable cost. In contrast, gas power induces low investment cost, yet, causes high variable cost from fuel sourcing. These costs are comparably lower for coal power, which is subject to low investment and fixed cost as well. The former type of costs is higher for wind power, which, however, hardly causes variable and fixed costs. Concerning wind power, its cost is furthermore driven by geographic circumstances. For example, the composition of total costs for offshore wind power comprises higher investment and fixed costs.

Note that, as Figure 1.2 depicts, coal power has low costs with respect to all three cost components. Furthermore, this technology can be dispatched and is hence independent of meteorological and geographic circumstances. The high competitiveness of coal power, without considering its external costs and its high abundance, can be seen as the main driver for its dominating role across power markets all over the world (Steckel et al., 2015).

Social costs With respect to social costs, the EU-REGEN framework includes policies that address the external effect from CO_2 emissions only. Yet, further environmental externalities, such as local air pollution from SO_2 as well as feedback effects on the power market are not considered. The same holds true for non-environmental externalities. Since the model setting does not represent the interaction between the power market and the rest of the economy, economic spillovers cannot be valued. Moreover, the EU-REGEN model yields the inter-temporal equilibrium by relying on perfect expectations. Consequently, the issue of technology lock-ins cannot be examined due to the perfect-foresight nature of the model. Similarly, the effects of market failure due to strategic investment and dispatch behavior cannot be evaluated in this model setting.

In general, externalities from electricity generation that cause social costs,[11] can be distinguished into environmental externalities and non-environmental externalities (Borenstein, 2012). Considering the social cost from environmental externalities that are not internalized by private firms can change a classification, as in Figure 1.2. There is scientific consensus that the emission of CO_2 into the atmosphere is one of the main drivers for the observed increase in global temperature (e.g., Cook et al., 2013, 2016). With power markets being one of the main emitters of CO_2, these emissions are one of the main environmental externalities from electricity generation.[12] If regulators introduce a policy instrument and hence producers internalize the social cost from CO_2 emissions, their variable cost for fossil fuel-based generation technologies will increase significantly. This mainly concerns coal power, which is highly competitive due to low private cost, but it suffers from high social cost due to its high carbon content.[13]

Note that extant research shows that the impact of power markets on climate change (mainly from CO_2 emissions) yields a feedback effect as well. The impact of climate change on power markets itself can be distinguished into effects on demand and supply (Mideksa and Kallbekken, 2010). Power generation could be impacted by reduced water supply from heat waves and droughts, which would influence hydropower directly and thermal power plants indirectly through lack of cooling water and the reduced efficiencies

[11] Social costs are production-related costs that are not internalized by private firms per se.

[12] Note that electricity and heat production caused 42% of global CO_2 emissions from fuel combustion in 2016 (IEA, 2018).

[13] The carbon content is the amount of carbon embedded in the fuel itself. The contained carbon is released through the combustion of the fuel. Then, it reacts with oxygen, and results in CO_2.

resulting from that (Rübbelke and Vögele, 2011; Golombek et al., 2012).[14] Moreover, increasing mean temperatures from climate change could alter electricity demand through a stronger correlation with temperatures. An example would be the increased adoption of air conditioning and, thus, soaring electricity demand (Auffhammer and Mansur, 2014).

However, there are more sources of environmental damage from electricity generation. Local environmental damages can comprise, for example, environmental degradation through fossil fuel extraction, loss of biodiversity, and local air pollution from fossil fuel combustion (e.g., Edenhofer et al., 2013).[15] Concerning the latter, pollutants such as nitrogen oxide (NO_x) and sulfur dioxide (SO_2) can cause local air pollution and enhance acid rain and smog (Owen, 2004).

Non-environmental externalities from electricity generation can create negative as well as positive impacts. One of the most prominent (negative) non-environmental externalities are path-dependences. Path-dependences in the power market are understood as the costs of locking an energy system into a subset of technologies due to, for example, the underlying infrastructure (Fouquet, 2016). Since investment in production and transmission infrastructure are characterized by long amortization periods, they can lead to slow adoption in the market and thus create inefficiencies. Moreover, both conventional generation technologies and RES, exhibit a negative externality on landscape aesthetics and, hence, property values (Davis, 2011; Gibbons, 2015).[16] Especially wind power can entail an externality through having a negative impact on human well-being (e.g., Krekel and Zerrahn, 2017).

Though, it is important to emphasize that there exist positive externalities as well such as employment effects, knowledge spillovers, and learning effects, among others (Edenhofer et al., 2013; Fouquet, 2016). With respect to employment effects, the large-scale investment and deployment of a new generation technology, for example, solar power, can lead to additional jobs in the energy sector and, thus, have a positive impact on the overall economy.[17] Innovation market failures, for example, knowledge spillovers, and learning effects, occur when since single firms, in the private optimum, do not account for their

[14] Note that in terms of wind power, changing climatic conditions could alter the temporal and geographic structure of wind resources. Yet, it cannot be generalized whether this leads to an overall positive or negative impact (Pryor and Barthelmie, 2010).

[15] See Samadi (2017) for a general overview of externalities from electricity generation.

[16] See Mattmann et al. (2016a,b); Dröes and Koster (2016); Chiabrando et al. (2009); Gamble and Downing (1982) for estimates on the impact of single technologies.

[17] Note that a higher number of workers in this sector is then mainly required due to the installation of capacities (Frondel et al., 2010). Thus, the nature of investments in RES, which are high up-front investment costs and low variable costs, questions to what extent this effect still holds in the long run (Borenstein, 2012).

impact on the knowledge stock of the economy and the development of future technology costs via their learning-by-doing (Fischer and Newell, 2008).

In this section, we described the general structure of the EU-REGEN model. Moreover, we outlined the type of costs that the framework considers for cost-minimization and, hence, a welfare-maximizing market outcome. In the following chapter, we will depict the numerical implementation of the cost-minimization problem with its set of constraints.

1.3 Numerical implementation

The EU-REGEN model is a linear program based on the US-REGEN model (Blanford et al., 2014).[18] In the following, we present the algebra of the model and use subscripts to refer to region r, time period t, time segment s, vintage v, generation technology i, storage technology j, natural gas supply class n, and biomass supply class b. The nomenclature of the sets, variables, and parameters used in this section are described in Table A.1 in Appendix A.1.

System costs The linear and deterministic optimization model minimizes the total discounted system cost c^{tot} (Equation (1.5)) that consists of investment costs for generation capacity $c^{\mathrm{gc}}_{r,t}$, transmission capacity $c^{\mathrm{tc}}_{r,t}$, storage capacity $c^{\mathrm{sc}}_{r,t}$, costs from generation operation $c^{\mathrm{vc}}_{r,t}$, maintenance costs for generation capacity $c^{\mathrm{fom}}_{r,t}$, and operation and maintenance costs for transmission $c^{\mathrm{tvo}}_{r,t}$ and $c^{\mathrm{tfm}}_{r,t}$:

$$c^{tot} = \sum_{r,t}[(c^{\mathrm{gc}}_{r,t} + c^{\mathrm{tc}}_{r,t} + c^{\mathrm{sc}}_{r,t}) \cdot tf_t + c^{\mathrm{vc}}_{r,t} + c^{\mathrm{fom}}_{r,t} + c^{\mathrm{tvo}}_{r,t} + c^{\mathrm{tfm}}_{r,t}] \cdot \mathrm{DF}_t \tag{1.5}$$

This includes the investment tax factor tf_t, which is determined by the investment tax rate TK and the length of time step t in years YR_t as well as the discount factor DF_t (Equation (1.6)):

$$tf_t = \frac{(1+\mathrm{TK})}{\mathrm{YR}_t} \qquad \forall t \in \mathcal{T} \tag{1.6}$$

In Equation (1.7), investment costs for generation capacity investments by firms $c^{\mathrm{gc}}_{r,t}$ are defined as a function of the new generation capacity $gc^{\mathrm{new}}_{i,r,t}$, its investment costs $\mathrm{IC}^{\mathrm{gc}}_{i,t}$, and the technology-specific lifetime factor $\mathrm{LF}_{i,v,r,t}$. The latter one is applied to avoid end-effects and adjusts investment costs for the share of the technology-specific lifetime

[18] See Young et al. (2013) and Blanford et al. (2014) for detailed information on the U.S. Regional Economy, Greenhouse Gas, and Energy (US-REGEN) model and carried-out analyses. Furthermore, note that the US-REGEN framework also captures the interaction between the power sector and other sectors of the economy.

that lies within the model horizon:

$$c^{\mathrm{gc}}_{r,t} = \sum_{i \in \mathcal{I}_{\mathrm{new}}} gc^{\mathrm{new}}_{i,r,t} \cdot \sum_{v} \mathrm{IC}^{\mathrm{gc}}_{i,t} \cdot \mathrm{LF}_{i,v,r,t} \qquad \forall r \in \mathcal{R}, t \in \mathcal{T} \tag{1.7}$$

Costs for new transmission capacity investment between regions undertaken by the central planner (Equation (1.8)) vary with the new transmission capacity $tc^{\mathrm{new}}_{r,rr,t}$ and the region-specific investments costs $\mathrm{IC}^{\mathrm{tc}}_{r,rr}$ that are a function of the distance between the regions' load centers or other geographic considerations as, for example, overseas connections:

$$c^{\mathrm{tc}}_{r,t} = \sum_{rr} tc^{\mathrm{new}}_{r,rr,t} \cdot \mathrm{IC}^{\mathrm{tc}}_{r,rr} \qquad \forall r \in \mathcal{R}, t \in \mathcal{T} \tag{1.8}$$

The last component of investment costs, electricity storage charge and discharge capacity, is described in Equation (1.9) by the product of the added capacity $sc^{\mathrm{new}}_{j,r,t}$ for storage technology j and the investment costs for storage charge capacity $\mathrm{IC}^{\mathrm{sc}}_{j}$:

$$c^{sc}_{r,t} = \sum_{j} sc^{\mathrm{new}}_{j,r,t} \cdot \mathrm{IC}^{\mathrm{sc}}_{j} \qquad \forall r \in \mathcal{R}, t \in \mathcal{T} \tag{1.9}$$

Costs from electricity generation operation and maintenance (O&M) by firms are represented by $c^{\mathrm{vc}}_{r,t}$ and $c^{\mathrm{fom}}_{r,t}$, respectively. In Equation (1.10), the variable dispatch costs are the specific variable operation costs $mc_{i,v,r,t}$ times the actual generation $g_{s,i,v,r,t}$ and the number of hours in each load segment H_s (see Section 1.6). We include costs from biomass separately by accounting for the cost $\mathrm{OC}^{\mathrm{bio}}_{b,r}$ from biomass supply $bs_{b,r,t}$:

$$c^{\mathrm{vc}}_{r,t} = \sum_{i,v} (mc_{i,v,r,t} \cdot \sum_{s} (g_{s,i,v,r,t} \cdot \mathrm{H}_s)) + \sum_{b} bs_{b,r,t} \cdot \mathrm{OC}^{\mathrm{bio}}_{b,r} \qquad r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{1.10}$$

A firm's marginal costs $mc_{i,v,r,t}$ comprise variable operation costs $\mathrm{OC}^{\mathrm{vom}}_{i,v,r}$, fuel costs, and costs from CO_2 permits (Equation (1.11)). Fuel costs vary with the fuel use coefficient $\mathrm{FC}_{i,f}$ (a binary variable allocating fuel type to generation technology), the technology-specific heat rate $\mathrm{HR}_{i,v,f,r}$ (with a lower heat rate indicating a more efficient combustion process), as well as time period and region-specific adjustment factors $\mathrm{FT}_{f,t}$ and $\mathrm{FR}_{f,r}$ (to account for, e.g., intra-regional fuel distribution costs). Costs from carbon permits are the product of emission intensity $\mathrm{EM}_{i,v,r}$ and the permit price PC_t:

$$\begin{aligned} mc_{i,v,r,t} = {} & \mathrm{OC}^{\mathrm{vom}}_{i,v,r} + \sum_{f} (\mathrm{FC}_{i,f} \cdot \mathrm{HR}_{i,v,f,r} \cdot (\mathrm{FT}_{f,t} + \mathrm{FR}_{f,r})) \\ & + \mathrm{EM}_{i,v,r} \cdot \mathrm{PC}_t \qquad \forall i \in \mathcal{I}, v \in \mathcal{V}, r \in \mathcal{R}, t \in \mathcal{T} \end{aligned} \tag{1.11}$$

Moreover, firms incur fixed O&M costs from holding generation capacity, costs characterized by the product of $gc_{i,v,r,t}$ and the fixed O&M costs $\mathrm{OC}^{\mathrm{fom}}_{i,r}$ (Equation (1.12)):

$$c^{\mathrm{fom}}_{r,t} = \sum_{i,v} \mathrm{OC}^{\mathrm{fom}}_{i,r} \cdot gc_{i,v,r,t} \qquad r \in \mathcal{R}, \forall t \in \mathcal{T} \tag{1.12}$$

In analogy, Equation (1.13) accounts for variable and fixed costs from electricity exchange between regions. With the variable costs $c^{\mathrm{tvo}}_{r,t}$ being the product of the transaction costs from physical flows $\mathrm{OC}^{\mathrm{tvo}}_{r,rr}$, the actual exchange between regions $e_{s,r,rr,t}$, and the number of hours in each load segment H_s. Fixed maintenance costs for transmission $c^{\mathrm{tfm}}_{r,t}$ are derived from the accumulated transmission capacity $tc_{r,rr,t}$ times the fixed costs for transmission $\mathrm{OC}^{\mathrm{tfm}}_{r,rr,t}$ (Equation (1.14)):

$$c^{\mathrm{tvo}}_{r,t} = \sum_{s,rr} \mathrm{OC}^{\mathrm{tvo}}_{r,rr} \cdot e_{s,r,rr,t} \cdot \mathrm{H}_s \qquad \forall r \in \mathcal{R}, t \in \mathcal{T} \tag{1.13}$$

$$c^{\mathrm{tfm}}_{r,t} = \sum_{rr} \mathrm{OC}^{\mathrm{tfm}}_{r,rr,t} \cdot tc_{r,rr,t} \qquad \forall r \in \mathcal{R}, t \in \mathcal{T} \tag{1.14}$$

Dispatch The main equilibrium constraint of a power market is to meet demand at any point in time. Accordingly, the market-clearing condition (Equation (1.15)) requires that generation $g_{s,i,v,r,t}$, plus electricity imports $e_{s,rr,r,t}$, less electricity exports $e_{s,r,rr,t}$, less electricity netexports to outside regions $\mathrm{E}^{\mathrm{int}}_{s,r}$, plus storage discharge $sd_{s,j,r,t}$, less storage charge $s_{s,j,r,t}$, and less self-consumption of hydro pump storage $\mathrm{PS}_{s,r}$ has to meet demand $\mathrm{D}_{s,r,t}$.[19] Moreover, flat loss factors are applied to account for losses from storage discharge ϵ and intra-regional distribution δ.[20] However, a region-specific loss factor is used for exchange between regions with $\mathrm{PEN}^{\mathrm{tr}}_{r,rr}$ being again a function of the distance between

[19] Note that this constraint does not allow for the curtailment of demand. An alternative approach would be allowing for demand curtailment by valuing unserved load at the price cap in the market, the value of lost load (VOLL) (e.g., Newbery, 2016). A too low set VOLL can trigger the so-called missing money problem where revenues do not fully cover cost (Joskow, 2013). Hence, the set-up of the EU-REGEN model excludes from the possibility of encountering the missing money problem.

[20] Note that the storage loss factor ϵ is applied only to the storage charge and consequently captures the losses occurring in the whole storage cycle.

the regions' load centers:[21]

$$
\begin{aligned}
&(\sum_{i,v} g_{s,i,v,r,t} + \sum_{rr} e_{s,rr,r,t} - \sum_{rr} e_{s,r,rr,t} \cdot \mathrm{PEN}^{\mathrm{tr}}_{r,rr} \\
&- \mathrm{E}^{\mathrm{int}}_{s,r} + \sum_{j} (sd_{s,j,r,t} - s_{s,j,r,t} \cdot (1-\epsilon)) \\
&- \mathrm{PS}_{s,r}) \cdot \mathrm{H}_s \\
&= \mathrm{D}_{s,r,t} \cdot \mathrm{H}_s * (1+\delta) \qquad \forall s \in \mathcal{S}, r \in \mathcal{R}, t \in \mathcal{T}
\end{aligned}
\tag{1.15}
$$

To account for physical constraints, generation of controllable generation units $g_{s,i,v,r,t}$, that are comprised in the set $\mathcal{I}_{\mathrm{ctr}}$, is limited by the installed capacity $gc_{i,v,r,t}$.[22] The latter is again constrained by an availability factor for each load segment $\mathrm{AF}_{s,i,r}$ (representing monthly availability patterns of dispatchable generation technologies) or a capacity factor $\mathrm{CF}_{s,i,r}$ for intermittent generation technologies (Equation (1.16)):

$$g_{s,i,v,r,t} \leq gc_{i,v,r,t} \cdot \mathrm{AF}_{s,i,r} \cdot \mathrm{CF}_{s,i,r} \qquad \forall s \in \mathcal{S}, i \in \mathcal{I}_{\mathrm{ctr}}, v \in \mathcal{V}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1.16}$$

To approximate observed generation patterns, we define certain must-run capacity by fixing generation at the average capacity factor for the set of non-dispatched generation technologies $\mathcal{I}_{\mathrm{fix}}$, that comprises, for example, geothermal power plants (Equation (1.17)):

$$g_{s,i,v,r,t} = gc_{i,v,r,t} \cdot \mathrm{AF}_{s,i,r} \cdot \mathrm{CF}_{s,i,r} \qquad \forall s \in \mathcal{S}, i \in \mathcal{I}_{\mathrm{fix}}, v \in \mathcal{V}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1.17}$$

With the same rationale we apply a lower bound to generation from nuclear power in Equation (1.18). We set the minimum nuclear generation to the dispatch factor DF_s of its available generation capacity:

$$g_{s,i,v,r,t} \geq gc_{i,v,r,t} \cdot \mathrm{AF}_{s,i,r} \cdot \mathrm{DF}_s \qquad \forall s \in \mathcal{S}, i \in \{nuclear\}, v \in \mathcal{V}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1.18}$$

Finally, we define, for notification purposes, total generation over all load segments in Equation (1.19) as

$$tg_{i,v,r,t} = \sum_{s} g_{s,i,v,r,t} \cdot \mathrm{H}_s \qquad \forall i \in \mathcal{I}, v \in \mathcal{V}, r \in \mathcal{R}, t \in \mathcal{T}. \tag{1.19}$$

[21] Note that the transmission loss factor $\mathrm{PEN}^{\mathrm{tr}}_{r,rr}$ is applied only to exports and hence captures the losses that occur in the exporting as well as the importing region.

[22] Note that the set of controllable generation units also comprises RES. However, the set excludes generation technologies that operate in multiple energy sectors such as combined heat and power (CHP) power plants.

Generation capacity With respect to the development of generation capacity over time, its accumulated capacity $gc_{i,r,t}$ is determined in Equation (1.20) as the sum of new generation capacity $gc^{\text{new}}_{i,r,t}$ in a specific period and the existing endowment in the previous period $gc_{i,v,r,t-1}$:

$$gc_{i,v,r,t} = gc^{\text{new}}_{i,r,t} + gc_{i,v,r,t-1} \qquad \forall i \in \mathcal{I}_{\text{new}}, v \in \mathcal{V}_{\text{new}}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1.20}$$

There are upper bounds to investment into new vintage technologies. A limit can be set to each region $\text{CAP}^{\text{gc}}_{i,r,t}$ and an additional one $\text{CAP}^{\text{geu}}_{i,t}$ to the system-wide investment in each technology, which approximates technical limits from the market for generation technologies (Equations (1.21) and (1.22)):

$$gc^{\text{new}}_{i,r,t} \leq \text{CAP}^{\text{gc}}_{i,r,t} \qquad \forall i \in \mathcal{I}_{\text{new}}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1.21}$$

$$\sum_r gc^{\text{new}}_{i,r,t} \leq \text{CAP}^{\text{geu}}_{i,t} \qquad \forall i \in \mathcal{I}_{\text{new}}, t \in \mathcal{T} \tag{1.22}$$

Retirement of generation capacity by firms is endogenous to the EU-REGEN model. New generation capacity has to be retired before its expected lifetime $\text{L}_{i,v,r,t}$, which is a binary variable with a positive number for each period before the time period of retirement at the latest (Equation (1.23)):

$$gc_{i,v,r,t} \leq gc^{\text{new}}_{i,r,t} \cdot \text{L}_{i,v,r,t} \qquad \forall i \in \mathcal{I}_{\text{new}}, v \in \mathcal{V}_{\text{new}}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1.23}$$

For existing capacity, in addition to retirement, there is the option of conversion and retrofits, which means allowing for the use of different fuels (e.g., biomass instead of coal) or the addition of a carbon capture facility to, for example, a coal power plant, respectively. We set upper bounds to conventional capacity that can be retrofitted (Equation (1.24)). Here, the amount of retrofitted capacity, which is determined by $gc_{i,v,r,t}$ and the retrofit factor RF_i, representing the capacity added through the retrofit, has to be below the capacity limit $\text{CAP}^{\text{ret}}_{i,r}$ (approximating technical limits) for the set of possible retrofit technologies $\mathcal{I}_{\text{ret}}$:

$$gc_{i,v,r,t} \cdot \text{RF}_i < \text{CAP}^{\text{ret}}_{i,r} \qquad \forall i \in \mathcal{I}_{\text{ret}}, v \in \mathcal{V}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1.24}$$

With respect to conversions, existing coal or lignite capacity can be used in conventional mode or converted to using different fuels. Hence, for the retirement of old capacity

$gc_{i,v,r,t}$,[23] the sum of old and converted capacity, which is scaled by the conversion factor CR_i (again representing the capacity added through the conversion), cannot exceed the amount of capacity that can still be operated based on the technical lifetime constraint(Equation (1.25)):

$$gc_{i,v,r,t} + \sum_{i \in \mathcal{I}_{\mathrm{cr}}} gc_{i,v,r,t} \cdot \mathrm{CR}_i \leq \mathrm{GC}^{\mathrm{old}}_{i,v,r} \cdot \mathrm{L}_{i,v,r,t} \qquad \forall i \in \mathcal{I}_{\mathrm{cr}}, v \in \mathcal{V}_{\mathrm{old}}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1.25}$$

Finally, as indicated in Equation (1.26), we make sure that generation capacity in each vintage retires monotonically decreasing:

$$gc_{i,v,r,t+1} \leq gc_{i,v,r,t} \qquad \forall i \in \mathcal{I}, v \in \mathcal{V}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1.26}$$

Storage The operation of electricity storage is constrained by the available storage and charge capacity. The former is determined by the sum of new capacity $sc^{\mathrm{new}}_{j,r,t}$ and existing capacity from the previous period $sc_{j,r,t-1}$ (Equation (1.27)):

$$sc_{s,r,t} = sc^{\mathrm{new}}_{j,r,t} + sc_{j,r,t-1} \qquad \forall j \in \mathcal{J}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1.27}$$

This charge capacity $sc_{j,r,t}$ is then the upper limit to the dispatch of storage charge $s_{s,j,r,t}$ and discharge $sd_{s,j,r,t}$, as depicted in Equations (1.28) and (1.29):

$$s_{s,j,r,t} \leq sc_{j,r,t} \qquad \forall s \in \mathcal{S}, j \in \mathcal{J}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1.28}$$

$$sd_{s,j,r,t} \leq sc_{j,r,t} \qquad \forall s \in \mathcal{S}, j \in \mathcal{J}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1.29}$$

Furthermore, Equation (1.30) limits the accumulated amount of stored electricity $sb_{s,j,r,t}$ to the storage capacity, which is determined by a fixed size SH_j (≥ 1) in relation to the charge capacity $sc_{j,r,t}$:

$$sb_{s,j,r,t} \leq \mathrm{SH}_j \cdot sc_{j,r,t} \qquad \forall s \in \mathcal{S}, j \in \mathcal{J}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1.30}$$

The dynamic accumulation of $sb_{s,j,r,t}$ is defined in Equation (1.31) as the amount of stored electricity in the previous time segment $sb_{s-1,j,r,t}$ plus the net charge, which is the difference between the storage charge $s_{s,j,r,t}$ and the storage discharge $sd_{s,j,r,t}$:

$$sb_{s,j,r,t} \leq sb_{s-1,j,r,t} + H_s \cdot (s_{s,j,r,t} - sd_{s,j,r,t}) \qquad \forall s \in \mathcal{S}, j \in \mathcal{J}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1.31}$$

[23] The parameter $gc_{i,v,r,t}$ captures all units operated in the base year.

Transmission As introduced in Section 1.2, the representation of electricity transmission in the EU-REGEN model is limited to exchange between regions. Its available capacity is the sum of new transmission capacity $tc^{\text{new}}_{i,r,t}$ and the capacity in the previous period $gc_{i,r,t-1}$ as shown in Equation (1.32):

$$tc_{r,rr,t} = tc^{\text{new}}_{r,rr,t} + tc_{r,rr,t-1} \qquad \forall r \in \mathcal{R}, t \in \mathcal{T} \tag{1.32}$$

To account for the political and technical feasibility of additions to transmission capacity, we set upper limits to it. For each time period, bounds can be applied to each individual connection between regions $\text{CAP}^{\text{tc}}_{r,rr,t}$ (Equation (1.33)) as well as to system-wide additions $\text{CAP}^{\text{teu}}_{t}$ in a specific time period (Equation (1.33)):

$$tc^{new}_{r,rr,t} < \text{CAP}^{\text{tc}}_{r,rr,t} \qquad \forall r \in \mathcal{R}, t \in \mathcal{T} \tag{1.33}$$

$$\sum_{r} tc^{new}_{r,rr,t} \cdot \text{TL}_{r,rr} < \text{CAP}^{\text{teu}}_{t} \qquad \forall t \in \mathcal{T} \tag{1.34}$$

Geologic storage of carbon The EU-REGEN framework allows for the geologic storage of CO_2 captured from electricity generation facilities.[24] For that purpose, the physical accumulation of the stored CO_2 is determined, as shown in Equation (1.35), by the product of capture rate CR_i, fuel coefficient FC_i, heat rate $\text{HR}_{i,f,r}$, fuel-specific carbon content CC_f, and generation $tg_{i,v,r,t}$

$$cs_{r,t} = \sum_{i,v,f} \text{CR}_i \cdot \text{FC}_i \cdot \text{HR}_{i,f,r} \cdot \text{CC}_f \cdot tg_{i,v,r,t} \qquad \forall r \in \mathcal{R}, t \in \mathcal{T} \tag{1.35}$$

with its dynamic accumulation being constrained in Equation (1.36) by the geological storage capacity $\text{CAP}^{\text{ccs}}_{r}$:

$$\sum_{r} cs_{r,t} < \text{CAP}^{\text{ccs}}_{r} \qquad \forall r \in \mathcal{R} \tag{1.36}$$

Resource constraints Furthermore, the dispatch and investment of generation technologies is limited by the availability of resources. With respect to wind and solar technologies, the limited availability of land area as well as competition with alternative land use types leads to limited potential within each resource class (see Section 1.5). As shown in Equations (1.37) and (1.38), for both groups of technologies, accumulated capacity additions and initial capacity $gc_{i,v,r,t}$ in each quality class, with $\text{QC}_{i,r}$ allocating existing capacities to quality classes, must not exceed the capacity limits $\text{CAP}^{\text{wind}}_{i,r}$ and $\text{CAP}^{\text{solar}}_{i,r}$

[24] Note that we only consider the storage of CO_2 and abstract from the depiction of the CO_2 transportation infrastructure.

(see Section 1.7):

$$\sum_{v} gc_{i,v,r,t} + \mathrm{QC}_{i,r} \cdot \sum_{v \in \mathcal{V}_{\mathrm{old}}} gc_{i,v,r,t} < \mathrm{CAP}^{\mathrm{wind}}_{i,r} \qquad \forall i \in \mathcal{I}_{\mathrm{wind}}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1.37}$$

$$\sum_{v} gc_{i,v,r,t} + \mathrm{QC}_{i,r} \cdot \sum_{v \in \mathcal{V}_{\mathrm{old}}} gc_{i,v,r,t} < \mathrm{CAP}^{\mathrm{solar}}_{i,r} \qquad \forall i \in \mathcal{I}_{\mathrm{solar}}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1.38}$$

Concerning biomass and gas, their availability is bounded by regional supply. As depicted in Equation (1.39), regional exogenous biomass supply $\mathrm{BS}_{b,r,t}$ is differentiated between supply classes b, which constrain biomass fuel use that is determined by the fuel use coefficient $\mathrm{FC}_{i,f}$, heat rate $\mathrm{HR}_{i,f,r}$, and annual generation $tg_{i,v,r,t}$ (see also Section 1.7):

$$\sum_{b} \mathrm{BS}_{b,r,t} \geq \sum_{i,v} \sum_{f \in \{bio\}} \mathrm{FC}_{i,f} \cdot HR_{i,f,r} \cdot tg_{i,v,r,t} \qquad \forall r \in \mathcal{R}, t \in \mathcal{T} \tag{1.39}$$

By analogy, gas demand is constrained in Equation (1.40) by exogenous gas supply $\mathrm{GS}_{g,r,t}$ over all gas supply classes g:

$$\sum_{g} \mathrm{GS}_{g,r,t} \geq \sum_{i,v} \sum_{f \in \{gas\}} \mathrm{FC}_{i,f} \cdot \mathrm{HR}_{i,f,r} \cdot tg_{i,v,r,t} \qquad \forall r \in \mathcal{R}, t \in \mathcal{T} \tag{1.40}$$

The CO_2 permit market As outlined in Section 1.2, the EU-REGEN framework addresses the environmental externality from fuel combustion by limiting the total amount of emissions and thus includes a market for CO_2 emissions from electricity generation.[25] In the default setting, the market for CO_2 permits does not allow for banking, that is, CO_2 emissions have to be offset in the period of occurrence. In that case, the amount of net banked credits nbc_t is set to zero. Meaning, in each period the amount of emitted carbon, which is characterized by the emission rate $\mathrm{EM}_{i,r}$ and total generation $tg_{i,v,r,t}$, cannot be above the CO_2 emission cap $\mathrm{CAP}^{\mathrm{co2}}_{t}$ (Equation (1.41)):[26]

$$\mathrm{CAP}^{\mathrm{co2}}_{t} - nbc_t \geq \sum_{i,v,r} \mathrm{EM}_{i,r} \cdot tg_{i,v,r,t} \qquad t \in \mathcal{T} \tag{1.41}$$

However, banking of permits can be allowed by introducing a banking market. Then, the banking market is modeled by the cumulative banked credits cbc_t, through the arithmetic

[25] Note that the model as well allows for introducing a carbon tax or exogenous carbon permit price (see Equation (1.11)).

[26] The magnitude of the CO_2 cap depends on the scenario of interest.

series indicated in Equation (1.42),

$$cbc_t = \sum_{t'<t} nbc_{t'} \qquad \forall t \in \mathcal{T} \tag{1.42}$$

including the constraint that accumulated banked credits balance by the model horizon (Equation (1.43)):

$$\sum_{t<2050} nbc_t = 0 \tag{1.43}$$

1.4 Model resolution

Spatial The EU-REGEN model represents the European power market. Its geographic scope includes all countries of the European Union (EU28), except for the island countries Malta and Cyprus. Additionally, the model includes Switzerland and Norway, which have a central position in the European system or are endowed with great resource potentials. To reduce the size of the model, those 28 countries are grouped into 13 model regions.[27] The aggregation is based on geographic characteristics and current configurations of the European power markets. However, Germany is disaggregated into a northern and southern region to reflect existing transmission limitations between the two regions—which triggered the current public debate on two pricing zones within Germany (e.g., Egerer et al., 2015, 2016). Figure 1.3 shows the EU-REGEN model regions.

Temporal The model horizon in the default model setting is 2050. We start with the base year 2015 (with given capacity) and optimize dispatch and investment in 5-year time steps up to 2050, which amounts to eight steps. Simulating dispatch on an hourly basis, or an even higher temporal resolution, offers the most accurate representation of power system operation. Yet, similar to the spatial aggregation described above, the number of time segments is reduced within each period for computational reasons. The default version of the model uses 121 intra-annual time segments. More information on the choice of representative hours can be found in Section 1.6. However, this reduced form approach means loss of the chronological order of hours and, thereby, compromises the modeling quality of, for example, electricity storage. Thus, electricity storage is only considered when looking at a single time period, where an hourly resolution is again feasible.

Technology The model includes 25 different types of generation capacity (see Table A.3 in Appendix A.2). To account for different characteristics of power plants of the same type or varying resource quality of variable RES, each type is further distinguished into

[27] See Table A.2 in Appendix A.2 for an overview of the composition of model regions.

Figure 1.3: EU-REGEN model regions and transmission links in the base year

generation blocks. This results in 73 different generation blocks by region with, for example, wind power making up for six blocks due to six different wind resource classes (see Section 1.5). Moreover, existing generation units are grouped into vintages to allow for different heat rates among generation blocks. Each vintage covers a period of five years and includes all units that went online in this period. New capacity can be added to each technology block through investment. Similar to existing installations, additions in different model periods are grouped into vintages to assign specific technological characteristics to each. As depicted in Section 1.3, generation capacity can be subject to upper bounds on additions or on accumulated capacity. Limits on additions are applied to nuclear power and accumulated capacity of each variable RES technology. Finally, the set of non-dispatchable technologies comprises geothermal and combined heat and power (CHP), and the set of technologies eligible for retrofit or conversion consists of hard coal, lignite, and gas power.

With respect to CCS, there is no commercially operated power plant in Europe as of now (EC, 2013b). In the model, new CCS generation technology can be added in combination with new generation capacity for lignite, coal, natural gas, or biomass power. Retrofits of existing conventional generation capacity is as well enabled for lignite, coal, and biomass power plants. Furthermore, the amount of captured CO_2 is subject to limited geological storage capacity.

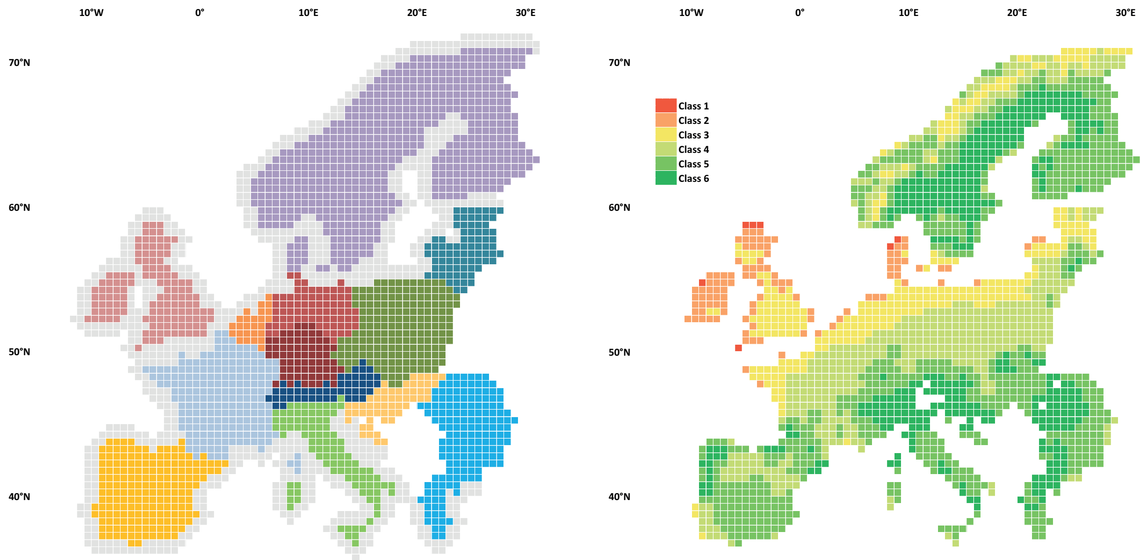
As indicated in Section 1.3, we abstract from intra-regional electricity distribution and model electricity exchange between regions only. We assume one generic type of transmission technology, whose investment costs, however, vary among regions to account for, for example, oversees connections. Existing transmission capacities between regions serve as starting values. In each time period, new transmission capacity can be added between neighboring regions or regions with an already existing transmission link. However, those additions are subject to upper bounds.

1.5 Modeling wind and solar technologies

The importance of a detailed representation of the intermittency of RES has been emphasized in, for example, Joskow (2011). The modeling of variable RES has to incorporate both components of the market value (see Section 1.2), the energy value and the demand-matching capability (Lamont, 2008). Yet, so far, little effort has been put into methodologies to capture the temporal, inter-, and intra-regional variations in a dynamic investment model. Our modeling approach accounts, on the one hand, for varying annual electricity generation from variable RES between and within regions. On the other hand, differences in the temporal profiles are captured. Therefore, the characteristics of the resources, wind speed, and solar irradiation, and their different technologies are captured in our modeling approach. In the following, we will outline the methodology for the detailed representation of variable RES in the EU-REGEN framework.

1.5.1 Resource data-base

To fully account for the intermittency and spatial variability of resources, the underlying data on wind and solar resources is required to be at a high temporal and spatial resolution. Similar to other studies (e.g., Cannon et al., 2015; Juruš et al., 2013; Olauson and Bergkvist, 2015), we use the MERRA (Modern-Era Retrospective analysis for Research and Applications) reanalysis data for both resources, which is provided by NASA (Rienecker et al., 2011). Parameters are available for the time interval between 1979 and today with a temporal resolution of 1 hour. The spatial resolution is $\frac{1}{2}$ and $\frac{1}{3}$ degree in latitude and longitude, respectively. Meaning, EU REGEN's geographic scope is covered by 2,704 locations, each one representing an area of $\frac{1}{2} \times \frac{1}{3}$ degree. Figure 1.4a illustrates the spatial resolution of the MERRA data set with different colors representing each model region and gray-colored grid cells indicating offshore area. For wind resources, we extract variables on eastward and northward wind speed at 50 meters above the surface (U50M and V50M), displacement height (DISPH), and roughness length (Z0M). Modeling solar power technologies is based on MERRA's surface incident shortwave flux (SWGDN) and the temperature 2 meters above displacement height (T2M) (NASA, 2010):



(a) Resolution **(b)** Distribution of wind resource classes

Figure 1.4: Wind resource data-base

1.5.2 Resource classes

As mentioned above, the EU-REGEN model captures the varying quality of variable RES through different generation blocks. The generation blocks of new variable RES vintages represent the different resource classes for each resource type. Concerning wind, we introduce six resource classes C_{wind} based on the wind speed at 100 m above ground. Classes are defined as shown in Table 1.1:

Table 1.1: Wind resource classes based on average wind speed at 100 m [m/s]

$Wind$ 6	$Wind$ 5	$Wind$ 4	$Wind$ 3	$Wind$ 2	$Wind$ 1
< 4	$4 - 5$	$5 - 6$	$6 - 7$	$7 - 8$	> 9

To determine the resource quality in each of the 2,704 locations, we calculate the average wind speed over the time period 1982 to 2013. By means of that measure, we allocate each location to one resource class within its region. An overview of the spatial distribution of resource classes is indicated in Figure 1.4b.

The same approach is applied to solar resources. Here, resource classes C_{solar} are based on the mean global horizontal irradiation from 1982 to 2013 (Table 1.2). Assigning a solar resource class to each location lead to the distribution shown in Figure A.1a in Appendix A.3.

Table 1.2: Solar resource classes based on average solar irradiation [kWh/m^2]

Solar 6	*Solar* 5	*Solar* 4	*Solar* 3	*Solar* 2	*Solar* 1
< 1,000	1,000 – 1,200	1,200 – 1,400	1,400 – 1,600	1,600 – 1,800	> 1,800

Due to its high investment costs, we assume concentrated solar power (CSP) to be suitable only for locations with high resource quality. Therefore, CSP is limited to locations within solar classes 1 and 2, as shown in Figure A.1b in Appendix A.3.

1.5.3 Wind power

In terms of wind power, we consider wind onshore and offshore as separate technologies. As of the end of 2016, 154 GW of cumulative wind power capacity was installed in the EU. A majority of 141 GW was installed onshore compared to 13 GW of offshore installations (Wind Europe, 2017). Moreover, cost and performance estimates of both technologies differ. Therefore, it is crucial to differentiate between them to capture the technological traits and economics of wind power.

Estimating the generation profile of wind power, which captures the availability of a wind power technology in each time segment, requires data on wind speed, displacement height, and surface roughness. The translation of these three input parameters into power output is based on three steps. First, the combination of wind speeds from two directions. Then, the extrapolation of wind speeds to hub heights. Finally, the translation of wind speeds for combinations of different hub heights and wind turbines to a normalized power output. We provdide a detailed elaboration of these steps in Section A.5 in Appendix A.5. Moreover, the nomenclature of the sets, variables, and parameters used in this section is described in Table A.4 in Appendix A.4.

However, the purpose of EU-REGEN requires region-wide profiles for existing and new vintages by resource class and, furthermore, profiles separated into onshore and offshore installations. In the following, we will outline the aggregation of profiles by locations to region-wide profiles for existing and new vintages.

Existing vintages For existing onshore vintages, we extrapolate wind speeds (see Equation (A.2) in Appendix A.5) to a hub height of 100 m and calculate the mean wind speed s_l^{m} over the time period from 1982 to 2013. This is used to assign locations l within each region to different site qualities $Q = \{low, medium, high\}$. Each site quality q is determined by upper limits s_q^{up} and lower limits s_q^{low} (Equation (1.44)):

$$\mathcal{L}_{\mathrm{q}} = \{(s_l^{\mathrm{m}} \geq s_q^{low}) \vee (s_l^{\mathrm{m}} \text{ł} s_q^{up})\} \qquad \forall l \in \mathcal{L}_{\mathrm{on}}, q \in \mathcal{Q} \tag{1.44}$$

Based on that, we calculate a weighted-average of the normalized wind power output $wp^{\text{trb}}_{s,l,h,g}$ in a region over all turbine types and locations $wp^{\text{hub}}_{s,h,q,r}$ (see Appendix A.5). This aims at approximating the current average configuration of an installed wind turbine in each region. Hence, we use, on the one hand, weights on the existing capacity distribution among sites within a region $W^{\text{wc}}_{l,r}$. On the other hand, we apply a weighting for the assumed existing technology-mix of hub heights and turbines within site qualities in each region $W^{\text{wt}}_{h,g,q,r}$:

$$wp^{\text{hub}}_{s,h,q,r} = \frac{\sum_g \sum_{l \in \mathcal{L}_{\text{on}}} W^{\text{wc}}_{l,r} \cdot W^{\text{wt}}_{h,g,q,r} \cdot wp^{\text{trb}}_{s,l,h,g}}{\sum_g \sum_{l \in \mathcal{L}_{\text{on}}} W^{\text{wc}}_{l,r} \cdot W^{\text{wt}}_{h,g,q,r}} \qquad \forall s \in \mathcal{S}, h \in \mathcal{H}_{\text{ex}}, q \in \mathcal{Q}, r \in \mathcal{R} \quad (1.45)$$

In a second step, we calculate the weighted average across hub heights and quality classes: ($W^{\text{hub}}_{h,q,r}$ and $W^{\text{q}}_{h,r}$) to get a single region-wide profile (Equation (1.46)). Furthermore, the turbine output is subject to loss factors σ^u and σ^p_s that represent a general loss and seasonal maintenance factor, respectively. So, we finally arrive at the normalized power output for each region and resource class:

$$wp^{on}_{s,r} = \sigma^u \cdot \sigma^p_s \cdot \frac{\sum_{h,q} W^{\text{q}}_{h,r} \cdot W^{\text{hub}}_{h,q,r} \cdot wp^{\text{hub}}_{s,h,q,r}}{\sum_{h,q} W^{\text{q}}_{h,r} \cdot W^{\text{hub}}_{h,q,r}} \qquad \forall s \in \mathcal{S}, r \in \mathcal{R} \quad (1.46)$$

We follow an analog approach for offshore applications. However, we abstract from different site qualities:

$$wp^{\text{hub-os}}_{s,h,r} = \frac{\sum_g \sum_{l \in \mathcal{L}_{\text{os}}} W^{\text{wc}}_{l,r} \cdot W^{\text{wto}}_{h,g,r} \cdot wp^{\text{trb}}_{s,l,h,g}}{\sum_g \sum_{l \in \mathcal{L}_{\text{os}}} W^{\text{wc}}_{l,r} \cdot W^{\text{wto}}_{h,g,r}} \qquad \forall s \in \mathcal{S}, h \in \mathcal{H}_{\text{ex}}, r \in \mathcal{R} \quad (1.47)$$

$$wp^{os}_{s,r} = \sigma^u \cdot \sigma^p_s \cdot \frac{\sum_h W^{\text{hub-os}}_{h,r} \cdot wp^{\text{hub}}_{s,h,r}}{\sum_h W^{\text{hub-os}}_{h,r}} \qquad \forall s \in \mathcal{S}, r \in \mathcal{R} \quad (1.48)$$

New vintages Concerning new on- and offshore vintages, we aggregate the output $wp^{\text{trb}}_{s,l,h,g}$ for each location to a single profile comprising all locations within each quality class C_{wind} in a region. The binary parameter $C^{\text{wind}}_{r,l,c}$ allocates each location to its resource class as depicted in Equation (1.49):

$$wp^{reg}_{s,r,c,h,g} = \frac{\sum_l wp^{\text{trb}}_{s,l,h,g} \cdot C^{wind}_{r,l,c}}{\sum_l C^{wind}_{r,l,c}} \qquad \forall s \in \mathcal{S}, r \in \mathcal{R}, c \in \mathcal{C}_{\text{wind}}, h \in \mathcal{H}_{\text{new}}, g \in \mathcal{G} \quad (1.49)$$

The final profile by region, quality class, and vintage is calculated by assuming a specific combination of hub-height and turbine type to each vintage year $W^{wind}_{r,h,g,v}$ (Equation (1.50)). We apply this approach to approximate technological progress. In analogy to existing installations, the loss factors σ^u and σ^p_s apply:

$$wp_{s,r,c} = \sigma^u \cdot \sigma^p_s \cdot \frac{\sum_{h,g} wp^{reg}_{s,r,c,h,g} \cdot W^{wind}_{r,h,g,v}}{\sum_{h,g} W^{wind}_{r,h,g,v}} \qquad \forall s \in \mathcal{S}, r \in \mathcal{R}, c \in \mathcal{C}_{\text{wind}} \tag{1.50}$$

Note that values of $wp_{s,r,c}$ directly yield into the capacity factor $\text{CF}_{s,i,r}$ introduced in Equation (1.16) in Section 1.3. Moreover, we approximate values for the parameters σ^u, σ^p_s, $W^{\text{hub-os}}_{h,r}$, $W^{\text{wc}}_{l,r}$, and $W^{\text{tec-os}}_{h,g,r}$ from the model calibration.

1.5.4 Solar power

With respect to solar power, we differentiate between three different types of solar power technologies: stationary photovoltaic (PV), tracking photovoltaic (PV-TK), and CSP. Currently, only PV is widely applied in Europe with 100 GW of installed capacity in 2016 (Eurostat, 2018). Yet, especially a long-term model on decarbonization paths, which is driven by the economics of generation technologies, should incorporate a great variety of solar power technologies. On the one hand, this allows for analyzing the impact of different relative costs among solar power technologies. On the other hand, PV, PV-TK, and CSP differ in their output profiles. This is due to the higher flexibility of PV-TK and CSP in terms of tracking and storage, respectively (Huld et al., 2008).

We can estimate generation profiles for solar power technologies by using direct and diffuse irradiance and ground temperature as input parameters. For all three technologies, the two main components of solar irradiation, direct and diffuse radiation flux, affect the output differently. Yet, solar irradiation data on a high spatial and temporal resolution is only reported for global horizontal irradiation (GHI). Hence, we have to separate the GHI into its direct and diffuse components before being able to estimate the power output. The methodology for separating solar irradiation in its components is explained in Appendix A.7. Moreover, the nomenclature of the sets, variables, and parameters used in this section is described in Table A.5 in Appendix A.6.

The conversion of the two components of solar irradiation and temperature to normalized output requires four main steps. We start by calculating the hourly angle of the sun's rays. This allows, in a second step, for calculating the overall solar irradiation at the module. Then, this has to be corrected for the panel efficiency and in a final step for the inverter efficiency. These steps result in the normalized solar power feed-in profile $sp_{s,l,o,p}$ by location and for different orientations o and tilts p. We provide a detailed description of these steps in Appendix A.8. In analogy to wind power, we derive different profiles for varying vintages and technologies of solar power in the following.

Existing vintages In a first step, profiles for existing PV installations are approximated in Equation (1.51) by weight $W^{\mathrm{sc}}_{l,r}$ for the existing capacity distribution among locations within a region on the normalized solar power output $sp_{s,l,o,p}$:[28]

$$sp^{reg}_{s,r,o,p} = \frac{\sum_l sp_{s,l,o,p} \cdot W^{\mathrm{sc}}_{l,r}}{\sum_l W^{\mathrm{sc}}_{l,r}} \qquad \forall s \in \mathcal{S}, r \in \mathcal{R}, o \in \mathcal{O}, p \in \mathcal{P} \tag{1.51}$$

Thereafter, we apply a distribution $W^{\mathrm{st}}_{o,p}$ for combinations of orientation and panel tilt to get a single profile by region (Equation (1.52)):

$$sp^{pv}_{s,r} = \frac{\sum_{o,p} sp^{reg}_{s,r,o,p} \cdot W^{\mathrm{st}}_{o,p}}{\sum_{o,p} W^{\mathrm{st}}_{o,p}} \qquad \forall s \in \mathcal{S}, r \in \mathcal{R} \tag{1.52}$$

New vintages For new static PV vintages, we assume a south-facing module with an optimal panel tilt based on Masters (2004). We aggregate the normalized solar power output $sp_{s,l,o,p}$ from Equation (A.26) in Appendix A.8 for each location to a single profile comprising all locations within quality classes C_{solar} and for each region as depicted in Equation (1.53). The binary parameter $C^{\mathrm{solar}}_{r,l,c}$ allocates each location to its resource class:

$$sp^{pv}_{s,i,r} = \frac{\sum_{o \in \{south\}} \sum_{p \in \{opt\}} \sum_l sp_{s,l,o,p} \cdot C^{solar}_{r,l,c}}{\sum_l C^{solar}_{l,c}} \qquad \forall s \in \mathcal{S}, i \in \{pv\}, r \in \mathcal{R} \tag{1.53}$$

New vintages of tracking PV are supposed to be single-axis, horizontally tracking systems with optimal tilting.[29] Thus, the output profile being calculated by

$$sp^{pv}_{s,i,r} = \frac{\sum_{p \in \{opt\}} \sum_l sp_{s,l,o,p} \cdot C^{solar}_{r,l,c}}{\sum_l C^{solar}_{l,c}} \qquad \forall s \in \mathcal{S}, i \in \{pvtk\}, r \in \mathcal{R}. \tag{1.54}$$

Again, $sp^{pv}_{s,r}$, $sp^{npv}_{s,i,r}$, $sp^{ntk}_{s,i,r}$ directly yields into the capacity factor $\mathrm{CF}_{s,i,r}$ of the model framework and values for $W^{\mathrm{sc}}_{l,r}$, $W^{\mathrm{st}}_{o,p}$, and $C^{solar}_{r,l,c}$ are derived from model calibration results.

Model for CSP power generation In contrast to PV technologies, CSP utilizes only direct normal irradiation $dni_{s,l}$ and includes a storage system. Due to the latter point, besides incoming radiation, the operation of a CSP system is influenced by electricity prices. For that purpose, we simulate the optimal dispatch of CSP based on prices from a static model run of the base year 2015 and derive a generation profile from that

[28] Note that we assume existing PV installations to be stationary only.

[29] Note that this means that the modules orientation α^2_o constantly equals the sun's azimuth angle $\alpha^1_{s,l}$ with Equation (A.17) in Appendix A.8 resolving to $\theta_{s,l,p} = \sin(\beta^1_{s,l}) \cdot \cos(\beta^2_{l,p})$.

optimization exercise, as done in Young et al. (2013). Moreover, the nomenclature of the sets, variables, and parameters used in this paragraph is described in Table A.6 in Appendix A.9.

We define the objective function (Equation (1.55)) as the revenue rev from CSP dispatch $g_{s,i,r}$ at prices $P_{s,r}$:

$$rev = \sum_{s,i,r} g_{s,i,r} \cdot P_{s,r} \tag{1.55}$$

Dispatch is constrained by the incoming irradiation $dni_{s,i,r}$, CSP storage charge $s^{csp}_{s,i,r}$, and discharge $sd^{csp}_{s,i,r}$ (Equation (1.56)) with the solar multiple SM being the relative size of the solar capacity to the CSP turbine capacity:

$$g_{s,i,r} \leq SM \cdot dni_{s,i,r} + sd^{csp}_{s,i,r} - s^{csp}_{s,i,r} \qquad \forall s \in \mathcal{S}, i \in \mathcal{I}_{\text{csp}}, r \in \mathcal{R} \tag{1.56}$$

Furthermore, the amount of stored electricity $sb^{csp}_{s,i,r}$ is limited by the storage capacity SH^{csp} in hours of turbine capacity (Equation (1.57))

$$sb^{csp}_{s,i,r} < SH^{csp} \qquad \forall s \in \mathcal{S}, i \in \mathcal{I}_{\text{csp}}, r \in \mathcal{R} \tag{1.57}$$

and its dynamic accumulation is defined as in Equation (1.58):

$$sb^{csp}_{s,i,r} = (1 - \epsilon^{csp}) \cdot sb^{csp}_{s-1,i,r} + s^{csp}_{s,i,r} - sd^{csp}_{s,i,r} \qquad \forall s \in \mathcal{S}, i \in \mathcal{I}_{\text{csp}}, r \in \mathcal{R} \tag{1.58}$$

We assume a storage loss of $\epsilon^{csp} = 0.05$, a solar multiple of $SM = 2.5$, and a storage capacity of $SH^{csp} = 6$ (Young et al., 2013).

1.6 Aggregation of time segments

Due to computational limitations, it is not feasible to run a dynamic dispatch and investment model with all 8,760 hours in each time period. Therefore, the number of time segments has to be reduced from 8,760 to a couple of hundred by choosing a subset of hours and weighting those. For that purpose we use a two-stage methodology developed for the US-REGEN model.[30]

First, the choice of representative hours is based on identifying the extreme values of the three dimensions per model region: normalized hourly electricity demand, wind, and solar

[30] See Blanford et al. (2018) for detailed information.

feed-in.[31] We identify the extreme values in all possible one-, two-, and three-dimensional spaces of wind, solar, and load. This means, for the one-dimensional spaces, we select the hours with minimum and maximum wind, solar, and load values (6 per region). With respect to the two-dimensional spaces, we select hours representing the vertices of all possible two-dimensional combinations of wind, solar, and load (12 per region). Finally, we select the eight vertices of the three-dimensional wind, solar, and load space (8 per region). With respect to the 16 regions used for the identification of representative hours, this would result in $26 \cdot 16 = 416$ extreme hours. However, some representative hours are an extreme in multiple regions, which reduces the number of hours already to 211. Furthermore, the algorithm is designed in such a way that it does not have to pick the hour with the most extreme values. Instead, it sets this particular hour as the vertex (in the three-dimensional space) and allows for choosing an hour that has a certain distance from the vertex. This allows us to reduce the number of required time segments to 121 when allowing for a distance of 1%.

Second, a weighting of representative hours is crucial to maintain the distribution of the hourly demand, wind, and solar profiles. Weights for each segment are chosen to minimize the sum of squared errors between the aggregated averages and the hourly averages across model regions for demand, wind, and solar profiles (Young et al., 2013).

1.7 Input data

Section 1.5 depicted how the input parameters for wind and solar power availability are derived. In the following, we provide an overview of the values of other main input parameters.

Generation technologies As mentioned in Section 1.4, we differentiate between 25 general types of generation technologies (Table A.3 in Appendix A.2). We use the UDI World Electric Power Plants Data-Base (Platts, 2013) to compile an inventory of each existing generation technology by vintage for each region. Estimates for heat rate by technology and vintage are based on model calibration and observed values. For the annual discount rate and investment tax rate, the model assumes rates of 7% and 30%, respectively. Availability factors for dispatchable generation technologies are derived from observed seasonal generation patterns (Eurostat, 2014) and the model calibration for the year 2012, which was chosen due to data availability reasons.

[31] We include an additional region for each of the model regions Britain, Iberia, and Scandinavia. For Iberia, we further include the existing feed-in from CSP. Concerning Britain and Iberia, we consider feed-in profils for future wind installations as well. Hence, we end up with 16 regions for the choice of representative hours.

The assumed lifetime is based on assumptions in IEA (2013) and holds for existing vintages as well as capacity additions within the model horizon. The same holds true for flat variable and fixed O&M cost with values taken from Schröder et al. (2013) (see Table A.7 in Appendix A.10 for both).

Assumptions on investment cost for vintages of new generation capacity (Table A.8 in Appendix A.10) are based on Schröder et al. (2013). We assume flat cost-curves for most conventional generation technologies. Costs for new RES and CCS capacity decrease over time, assuming cost-reductions through learning and economies of scale (Table A.8 Appendix A.10). The costs for tracking photovoltaic installations are derived from those of static photovoltaic by adding a 25% mark-up.

Concerning investment into dispatchable generation technologies, we set specific public attitudes and capacity limits for nuclear power in each region as a default. In general, capacity additions of nuclear power are not allowed in the following regions in any time period: Benelux, Germany-N, Germany-S, Iberia, Alpine, and Italy. Moreover, based on projected commissioning dates of current units under construction from World Nuclear Association (2014), nuclear power plant capacities of 1.75 GW for France, 1.7 GW for Scandinavia, and 0.94 GW for Eastern Europe-NW are assumed to be complete by 2020. After 2020, capacity additions are unconstrained in regions eligible for nuclear power additions.

Table 1.3: Overview of fuel prices and carbon contents

Fuel type	Fuel price [€/MWh]	Carbon content [tCO2/GJ]
Lignite	3.5	0.099
Coal	14	0.094
Natural gas	33.5	0.056
Oil	64	0.074
Biomass	17 – 36	0.099

Fuel-powered generation technologies in the EU-REGEN model either require lignite, coal, natural gas, oil, or biomass. We apply system-wide and flat fuel prices that are subject to regional adjustment factors (IEA, 2012). For biomass, cost varies for different biomass supply classes to approximate an upward-sloped supply curve (Section 1.7). The fuel-specific carbon content and basic fuel prices are indicated in Table 1.3.

Wind and solar potentials In addition to the resource class specific time-profiles described in Section 1.5, the detailed representation of variable RES requires data on the capacity potentials in each of those classes, that is, the maximum amount of accumulated capacity. The potential capacity by resource class depends on a variety of factors, for example, exclusion areas, siting constraints, and local topography. Therefore, we use data provided by AWS Truepower (AWS). AWS uses a two-stage approach to provide separate potential values for wind onshore, wind offshore, utility-scale solar, and distributed solar applications. In a first step, an extended geographic-information-system (GIS) analysis is carried out to determine the area that is actually available to the deployment of wind power. This is followed by estimating the capacity of power plants that could be installed in this area by assuming a certain capacity density by area of available land. Values are calculated for each of the above-mentioned applications, resource classes, and model regions. An overview of the sum of capacity potential over resource classes by variable RES and region is presented in Table 1.4.

Table 1.4: Upper limits on variable RES capacities [GW]

Region	Wind-on	Wind-os	PV
Britain	238	74	366
France	203	2	653
Benelux	15	32	94
Germany-N	69	11	236
Germany-S	61	-	217
Scandinavia	673	26	677
Iberia	190	-	556
Alpine	30	-	77
Italy	133	-	254
Eastern Europe-NW	276	-	512
Eastern Europe-NE	93	-	196
Eastern Europe-SW	78	-	218
Eastern Europe-SE	134	-	437

Note: We show aggregated values for property right reasons.

Biomass potentials As indicated above, we approximate the limited supply of biomass for electricity generation with four biomass supply classes. The biomass energy potential for each country and each of these classes is estimated based on numbers from Elbersen et al. (2012). Similar to Bruninx et al. (2015), we group different kinds of biomass to each supply class: ranging from class 1, which comprises cheap and local resources, to class 4 with industrially grown energy crops. Table 1.5 shows an overview of the composition of biomass supply classes. Moreover, as done in Nahmmacher et al. (2014), we assume 50% of biomass energy potential to be available for the power market.

Demand We introduced in Section 1.2 that EU-REGEN's demand side is modeled exogenously. We assume the 2012 hourly electricity demand pattern (ENTSO-E, 2014c) to be valid for future time periods as well. Moreover, we use 2012 values since it can be assumed that these include little shifting and shedding of demand by consumers (see

Table 1.5: Overview of biomass supply classes

Class	Biomass resources
Class 1	Tertiary waste residues
Class 2	Secondary agricultural and forestry residues
Class 3	Primary agricultural, forestry, and waste residues
Class 4	Forestry biomass and energy crops

also Chapter 3). The estimates for country-specific annual electricity demand levels are taken from projections from the *e-HIGHWAY 2050 Project* (Bruninx et al., 2015) with a system-wide demand level of 4,324 TWh for 2050. This is consistent with the 4,300 TWh in the EC's "Trends to 2050" reference scenario (EC, 2013a) and translates into a demand growth of 34% compared to 2015 with 3,223 TWh. Regional growth rates are subject to great differences, ranging from a 25% reduction for Norway to a 311% increase in the case of Lithuania. Moreover, growth patterns between 2015 and 2050 are assumed to follow a linear path. An overview of 2015 and 2050 demand levels with growth rates is given in Table A.9 in Appendix A.10. However, due to the electrification of other sectors, it can be assumed that electricity demand increases even stronger. The EC assumes in his impact assessment on the "[...] policy framework for climate and energy in the period from 2020 up to 2030" that electricity generation reaches a level of 5,050 TWh in 2050 (EC, 2014). Thus, we scale growth rates from Bruninx et al. (2015) to reach this demand level and use this electricity demand path as an alternative.

Transmission For variable costs of electricity exchange between regions, we assume costs of 0.5 €/MWh. Similar to Schaber et al. (2012), region-specific costs for capacity additions are calculated based on investment costs of 2.4 mio. €/km for a capacity of 6.4 GW and scaled to the distance of population centroids of two regions. Furthermore, we use a loss factor of 0.04 per 1000 km for trade flows between regions. Loss factors from intra-regional distribution are approximated from reported losses (Eurostat, 2014).

Values for existing transmission capacities, or net transfer capacities (NTC), between regions are based on the ENTSO-E NTC values (ENTSO-E, 2014b) and are shown in Table A.10 in Appendix A.10. The 16 GW of existing transfer capacity between both German regions are based on Bundesnetzagentur (2012, 2015). Moroever, as mentioned in Section 1.3, we assume upper bounds on new transmission capacity in each time period. Values are based on estimations from the ENTSO-E "10-Year Network Development Plan" ENTSO-E (2014a) and results of the *SUSPLAN Project* (de Joode et al., 2011) and extrapolated to future periods. As an example, Tables A.11 and A.12 in Appendix A.10 show the investment limits for 2030 and 2050.

Carbon capture and storage Upper bounds for the geologic storage of CO_2 are estimated from work done within the *EU GeoCapacity Project* (Vangkilde-Pedersen et al., 2009). We accumulate storage capacities of different geologic formations and countries into a single value for each model region (Table 1.6).

Table 1.6: Overview of limits for geologic storage of CO_2 [Gt CO_2]

Britain	*France*	*Benelux*	*Ger-N*	*Ger-S*	*Scanda*	*Iberia*
14.4	8.69	2.54	9.14	7.94	31.94	1.58
Alpine	*Italy*	*EE-NW*	*EE-NE*	*EE-SW*	*EE-SE*	-
-	6.55	5.51	0.44	3.61	11.37	-

1.8 Model application

The EU-REGEN model is able to implement policies addressing the various components of the power market. Based on the scenario-specific set-up, additional constraints on generation technologies, transmission infrastructure, the CO_2 emission budget, and CCS, among others, can be introduced. In the following, we present the set-up of a market-wide 80% and 95% CO_2 emission reduction scenario and show results for the development of system-wide generation-mixes and generation capacities.

1.8.1 Scenario set-up

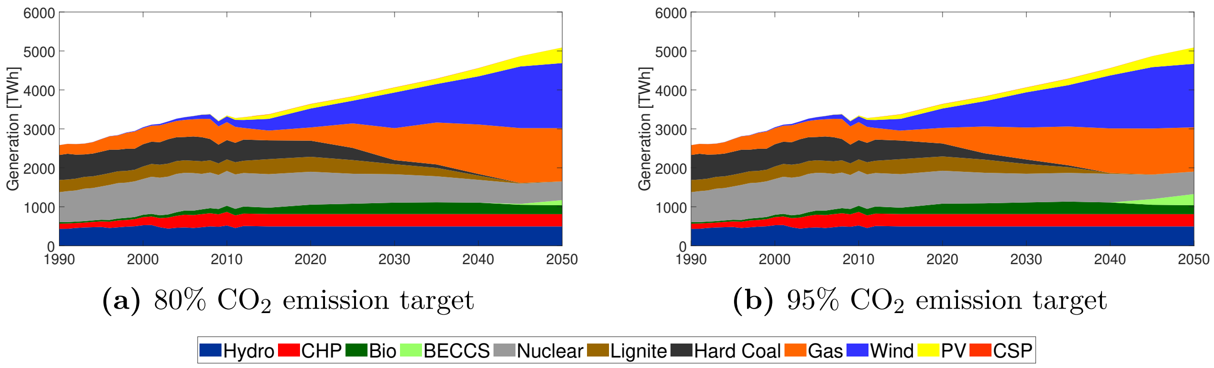
The *80% CO_2 emission reduction scenario* is based on the energy and climate policy brought forward by the EC. The long-run targets were specified by an 80% CO_2 emission reduction for the entire economy overall in 2050 (EC, 2011a,b). In the mid-run, a 40% reduction of CO_2 emissions is aimed for 2030 (EC, 2014). We implement these targets through annual CO_2 emission budgets. For the time-steps in between, we assume a linearly decreasing CO_2 emission budget. Furthermore, we assume electricity demand to increase linearly to 5,050 TWh in 2050 (see Section 1.7).

However, the EC showed in its impact assessments, that the power market has to overreach the 80% CO_2 emission reduction target due to higher marginal abatement costs in other sectors (EC, 2014). Hence, we additionally present a *95% CO_2 emission reduction scenario*. Again, we implement this target by annual CO_2 emission budgets. We assume annual CO_2 emission budgets that decrease linearly from the 2015 level to a 95% CO_2 emission reduction in 2050.[32]

[32] All CO_2 emission reduction targets are related to 1990 levels.

1.8.2 Results

Results for the cost-efficient generation path in the 80% CO_2 emissions reduction scenario are depicted in Figure 1.5a. The future generation-mix for the European power market is driven by the interplay between wind and gas power. Wind power becomes the main generation technology with a generation-share above 20% by 2030 and above 30% by 2050. The intermittency of its generation profile is compensated for by the increasing market penetration by flexible gas power generation technologies. Hence, gas power reaches a generation-share above 25% by 2050. Other RES—biomass and photovoltaic power—play a minor role in this scenario. Only photovoltaic power gains a higher generation-share by the end of the scenario horizon. The market-share of the currently main dispatchable generation technologies, that is, coal, lignite, and nuclear power, decreases significantly. For coal and lignite power, this is driven by the high carbon content of the fuel, which contradicts the CO_2 emissions target in this scenario. However, both technologies still contribute to meeting demand in 2050. In terms of nuclear power, high investment costs do not allow for new investments in a cost-efficient path. Interestingly, biomass in combination with CCS (BECCS) already plays a role in this 80% scenario. The high generation-share of gas power that compensates for the intermittence of RES comes at the cost of CO_2 emissions. Hence, the negative emissions from BECCS are still necessary to meet the climate target.



(a) 80% CO_2 emission target

(b) 95% CO_2 emission target

Figure 1.5: Long-run generation path with 80% and 95% CO_2 emission reduction target

Note: Both Figures further include the historic generation-mix from 1990 to 2015.

The generation path in the 95% CO_2 emissions reduction scenario is shown in Figure 1.5b. Comparing the generation paths in both scenarios shows that there is one major channel, the substitution of gas power by BECCS, to reach the more ambitious target. The generation from gas power is reduced to a level below 22% by 2050. This is compensated for by the increased contribution of BECCS. In terms of emissions, the higher target is reached by reduced emissions from gas power, on the one hand, and the high negative emissions from BECCS, on the other hand. The generation from all other technologies does not change significantly between the two scenarios.[33]

1.9 Outlook

The EU REGEN provides a long-run dispatch and investment model for the European power market. The model contributes with a detailed representations of wind and solar electricity generation technologies, which are characterized by a spatially varying, intermittent supply pattern. This is implemented by introducing different quality classes for wind and solar resources in the competitive equilibrium setting of a partial-equilibrium power market model. Moreover, we provide in this chapter a routine for processing meteorological parameters to capture the intermittency of RES.

Our results for the long-run market equilibrium show that, under an 80% CO_2 emissions reduction scenario until 2050, RES become the major group of technologies. Wind and photovoltaic power together reach a 2050 market-share of approximately 40%. The intermittency of RES comes at the cost of an increasing market-share of gas-powered technologies, which in turn results in emitting CO_2. Thus, the market entrance of biomass in combination with CCS is necessary to reach the CO_2 constraint in this scenario. Comparing this to a 95% CO_2 emissions reduction scenario, we find that BECCS, which has a negative emission intensity, substitutes CO_2-emitting gas power.

All in all, our findings suggest that even though accounting for the temporal and spatial characteristics of RES, the projected growth of RES is cost-efficient. The detailed depiction of their characteristics rather impacts the composition of the remaining supply stack, which mainly provides flexibility. However, our results should also be analyzed in view of the social phenomena connected to wind power. We showed in Section 1.2 that there is empirical evidence for the existence of a negative externality from the physical presence of wind turbines. Accordingly, apart from its cost prospects and meteorological characteristics, the dominating role of wind power crucially depends on to what extent regulators can manage its negative externalities, and resulting social acceptance issues.

[33] See Figures A.3a and A.3b in Appendix A.11 for the cost-efficient capacity investment path for both scenarios.

Chapter 2

Decarbonization of Power Markets under Stability and Fairness: Do They Influence Efficiency?

2.1 Introduction

The creation of a decarbonized economy with a fully integrated energy market is one of the main goals of the European Commission's (EC) *Energy Union*, which purpose is to coordinate the transformation of the European energy supply (EC, 2015). In terms of power markets, this means the creation of a single European market to keep the cost of transformation at a bearable level. This corresponds to the first-best solution from economic theory. If a group of players is subject to a market-wide and binding constraint, coordination allows them to reach the cost-effective allocation. Meaning, if players can coordinate and share information, they are able to reach the first-best outcome (see Montgomery, 1972). In the context of power markets this translates into regions that try to maximize their welfare in the power market with respect to a climate (carbon) target. Regions coordinate their abatement efforts until marginal abatement cost across all regions are equal. If regions fail to coordinate, average abatement cost increase, which results in a welfare loss.

Yet, EU member countries started to announce additional national climate and energy targets.[1] For instance, Germany aims at a reduction of the economy-wide CO_2 emissions of at least 80% by 2050 (BMWi, 2010). Similarly, France introduced a law on the transition of its power sector limiting the share of generation from nuclear power to 50% from 2025 on and targeting a CO_2 emission reduction of 50% by 2030 and 80% by 2050 (Assemblée Nationale, 2015).[2] These national climate targets indicate a certain degree of self-interest and are an additional source of disturbance. This shows that single regions or countries pursue power market-specific objectives that go beyond economic efficiency in general. It is assumed that competitive markets yield the cost-effective supply of electricity. Yet, the private optimum does not consider social costs that evolve from power market externalities. In addition to environmental issues, regulators want to address further objectives with respect to energy markets (Gillingham and Sweeney, 2010). These can comprise energy independence (Gillingham and Sweeney, 2010), resource adequacy (Paulus et al., 2011), energy security (Guivarch and Monjon, 2017), employment effects (Roques, 2008), technological innovation (Frondel et al., 2010), and redistributive effects (Egerer et al., 2016).

Redistributive effects lead to the phenomenon that *cooperation* is not always rational from the perspective of a single region. The maximization of overall welfare through coopera-

[1] See, e.g., the *IEA/IRENA Global Renewable Energy Policies and Measures Database* for an overview of existing national climate targets (of EU member countries). It can be accessed under https://www.iea.org/policiesandmeasures/renewableenergy/.

[2] All CO_2 emissions reduction targets stated in this paragraph refer to 1990 levels.

tion leads to redistribution and can result in a reduction of a region's welfare compared to the case without cooperation. This reflects the trade-off between economic efficiency and redistribution that is often referred to in climate and energy economics (Edenhofer et al., 2013). Here, redistribution can be examined between geographic regions or producers and consumers, among others. In general, it is important to discuss distributional effects to promote broad acceptance for climate policies and to avoid lock-ins into inefficient paths (Strunz et al., 2016).

So far, the perspective on redistributive issues in power markets has focused on the market power of individual firms. For example, Hirth and Ueckerdt (2013) analysis on the effect of renewable energy sources (RES) support schemes and CO_2 emission pricing on redistributive flows between producers and consumers in power markets. Similarly, Joskow and Tirole (2000) investigation of the presence of market power of generators and consumers in the context of transmission rights, while Borenstein et al. (1999) analyzing to what degree market power is exercised in the Californian power market at plant level.

The behavior of countries or regions has, to the best of the authors knowledge, only been researched by Gately (1974), Nylund (2014), Schlachtberger et al. (2017), and Huppmann and Egerer (2015). Gately (1974) looks at the distribution of gains from regional cooperation in the case of the Indian power market. This analysis is based on the theory of cooperative games. In analogy, Nylund (2014) elaborates on the regional effects of cooperation in the northern European power market. The authors in Schlachtberger et al. (2017) analyze the importance of cooperation by setting different levels of cross-boarder transmission capacity. A more advanced approach is implemented by Huppmann and Egerer (2015), which endeavors to find the Nash equilibrium between zonal planners that maximize their welfare from transmission capacity investments.

The chapter at hand adds to this by an extended application of *cooperative game theory* and hence tries to apply a bottom-up model in a framework that looks beyond a single market-wide optimum.[3] The aim of the analysis is to quantify the impact of fairness considerations on the equilibrium path of the EU power market.[4] Therefore, the following research questions will be answered: First, how does the first-best outcome manifest in quantities and prices? Second, why is it not rational from the perspective of individual countries to cooperate with respect to a common carbon budget? Third, how would an equilibrium look if regions refuse to enter coalitions that are not rational? Finally, how

[3] A similar research approach has been taken in other fields, e.g., by Bréchet et al. (2011) and Massol and Tchung-Ming (2010).

[4] The analysis in this chapter exclusively focuses on cooperation within the European power market and does not consider other markets or regions outside of Europe as in, e.g., Carraro and Siniscalco (1992).

can fairness be improved if it is derived from rational behavior or the relative importance of each region?

In general, power markets allow for (at least) two channels of cooperation between regions. First, the utilization of cooperative advantages with respect to abatement cost. Regions, that form a coalition, can shift emission reductions among them and hence individual regions (within a coalition) can exceed or fall below their emission budget (compared to the case of national emission budgets). This is closely related to the concept of international environmental agreements (IEAs) (see Carraro and Siniscalco, 1993; Barrett, 1994), where regions form coalitions to jointly set a carbon target. Yet, in the case of IEAs, regions outside a coalition maximize their welfare without setting a climate target. Thus, there exists the possibility of side payments to create economic incentives for regions outside a coalition to reduce emissions (Hoel and Schneider, 1997).

Second, regions cooperate for the sake of providing electricity at low marginal cost (excluding cost for emission certificates) and thus engage in cross-boarder electricity trade. This mainly refers to the utilization of comparative advantage and is in line with the market efficiency rationale of trade agreements in general (e.g., Baier and Bergstrand, 2004) and power market integration in particular (e.g., Jamasb and Pollitt, 2005).[5] In general, the economic motive for trade agreements assumes that the exchange of goods and services is mutually beneficial. Nonetheless, economic incentives for international trade can be set, for example, in the form of foreign direct investments or counter trade (Marin and Schnitzer, 1998).

The extent of cooperation in this chapter primarily aims at the sharing of *emission budgets*. Regions form coalitions to utilize the most efficient abatement sources under a common CO_2 emissions reduction target. This is equal to the introduction of a single market price for emissions and leads to a shift in the distribution of costs among regions. Hence, cooperation does not have to be rational *per se*. These distributional consequences with respect to benefits and costs of the introduction of such a uniform price signal are well-known from environmental economics. Moreover, this chapter assumes that regions outside the coalition of interest set their own carbon target, which can be well motivated by the national climate policies that are already existing and were mentioned for the case of Germany and France above. However, it is assumed that the market under consideration, nonetheless, fulfills the properties of a perfect market and regions engage in cross-boarder electricity trade.

[5] Apart from utilizing differences in marginal cost of generating electricity, cross-boarder electricity trade is also a consequence of balancing demand and supply of electricity, which can be stored under high cost only (Abrell and Rausch, 2016).

Having these assumptions in mind, the framework of cooperative game theory is suitable for analyzing this type of cooperation for two reasons: First, the relevant concepts of *gain-sharing* can still be applied while maintaining the efficient solution approach of a bottom-up power market model. Second, the equilibrium outcome for different coalitions can be compared with respect to a variety of market variables, for example, capacity investment path, and the approach can thus go beyond a pure cost perspective.

For this analysis, the EU-REGEN model is applied to find the long-run equilibrium for the European power market under a tight climate policy. Results indicate, that in the absence of transfer payments only a small share of the gains from full cooperation can be maintained. Hence, this chapter shows that the phenomenon of only small-sized coalitions being stable, also holds for the power market. Moreover, the analysis indicates that accounting for fairness goes in hand with balancing robustness against cost changes and individual rationality or core stability, respectively. This implies for the policy setting of the EU that future regulation should include transparent transfer schemes to facilitate the efficient implementation of a transformation path.

The chapter is organized in the following way. To begin, Section 2.2 provides an overview of the game theoretic framework and the quantification of costs in this chapter. Then, Section 2.3 presents the respective results. Finally, the chapter closes with a discussion of the applied methodology and a conclusion in Section 2.4.

2.2 Methodology

This section presents the game theoretic framework, the relevant solution concepts, and the quantification of costs used in this analysis.

2.2.1 Framework

This chapter assumes a cooperative game framework,[6] which generally describes the bargaining problem of coalitions with a focus on identifying feasible and stable coalitions

[6] In general, the interaction between players can be distinguished into cooperative and non-cooperative games. Cooperative games focus on payoffs from cooperation, whereas the latter mainly addresses the strategic actions of players. Non-cooperative games capture the strategic interaction of players, which aim at optimizing their payoff function. Each player's strategy of the choice variable is a function of the available information. One prominent solution concept to non-cooperative games is the Nash equilibrium. It is based on the notion of best responses. Each player chooses his choice variable under the belief that the choice of the other players is given. Accordingly, a solution is stable if no player has the incentive to deviate from her action under the assumption that all other players keep their choice constant.

and distributing the gains from cooperation (Ray and Vohra, 2015).[7] The coalition game is characterized by the player set $N := \{1, ..., n\}$ and the function $v : 2^n \to \mathbb{R}$ that assigns a value $v(S)$ to each coalition. Coalitions are the non-empty subsets $S \subseteq N$ with N being the *grand coalition* and $\{i\}$ the *singleton coalitions*.

In the context of this chapter, the regions of the European power market are regarded as the set of players N. The analysis looks at $2^n - 1 - n$ possible coalitions,[8] which comprise the grand coalition N that represents the first-best outcome with full cooperation and, thus, the cost-efficient market equilibrium.

Moreover, the permutation $c \in \mathbb{R}^n$ assigns cost $c_i(S)$ to each player. The cost of player i with being in a coalition and if the initial cost allocation is realized is $c_i(S)$. On the contrary, $c_i(\{i\})$ is the cost of i under singleton coalitions only. The cooperative cost-sharing game is assumed to still meet the properties of a perfect market. Hence, even though coalitions $S \subset N$ are in place, finding the market-wide cost minimum is regarded as a valid solution approach and when two neighboring regions are not comprised in a coalition, cross-boarder flows of electricity are still feasible. Consequently, a respective (climate) coalition can have minor impacts on regions that are not comprised. However, for the sake of simplicity and to be in line with the formalism of cooperative games, the remainder of this chapter assumes that regions outside a coalition are confronted with the cost under the singleton coalitions only case $c_i(\{i\})$. Hence, this chapter works with the (N, v) characteristic function (von Neumann et al., 1944), which maps coalition structures to individual cost for all players $i \in S$.[9] Moreover, the game can be transfered into a cost-saving game by defining the value of a coalition $v(S)$ as the sum over the cost-savings from all members of a coalition:

$$v(S) = \sum_{i \in S} (c_i(\{i\}) - c_i(S)) \quad \forall\, S \subseteq N$$

Furthermore, this chapter distinguishes between transferable utility (TU) games and non-transferable utility (NTU) games. In terms of TU games, the total gain from cooperation $v(S)$ can be transfered between players. This is based on the assumptions that utilities are expressed in units of a common numeraire good and utility functions are quasilinear. In this case, coalitional games aim at maximizing the worth of the coalition $v(S)$. In

[7] The same rationale applies to games where players share payoffs instead of costs.

[8] In general, n players can form $2^n - 1$ non-empty coalitions. Yet, this number also comprises n singleton coalitions of cardinality $|S| = 1$. Consequently, the number of $2^n - 1$ coalitions is corrected for the n singleton coalitions.

[9] An alternative concept is the partition function (Thrall and Lucas, 1963), which considers the cost to all players $i \in N$.

contrast to that, NTU games do not allow for transfer payments between players. Hence, it is the goal of the game to find the coalitional setting with the Pareto-optimal cost distribution.

This chapter assumes TU games to be superadditive.[10] So, the sum of the value of two disjoint coalitions is strictly smaller than the value of the grand coalition, which comprises the players of both coalitions (Rothe and Rothe, 2015):

$$v(s_1 \cup s_2) > v(s_1) + v(s_2)$$

2.2.2 Solution concepts

Solution concepts to cooperative games can be distinguished with respect to the underlying requirements on cooperation. This analysis focuses on concepts addressing stability and fairness.

2.2.2.1 Stability concepts

Concepts of stability rather look at the stability of each individual coalition S than just at the grand coalition N. For that purpose, the cost distribution $\hat{x}_i(S)$ of the total cost is defined as the first-best cost incurred by a given player i if coalition S is formed.

Internal and external stability The notion of *internal and external stability* was introduced in d'Aspremont et al. (1983) and d'Aspremont and Gabszewicz (1986) and further applied in, for example, Barrett (1994). Accordingly, a coalition S is stable if the cost distribution meets the criteria of internal and external stability. Concerning the former one, a coalition is stable if no member of a coalition has the incentive to stay outside the coalition:[11]

$$\hat{x}_i(S) \leq c_i(S \setminus \{i\}) \quad \forall\, i \in S$$

For the latter one, no player outside the coalition prefers to join the coalition, which can be formalized as

$$c_i(S) \leq \hat{x}_i(S \cup \{i\}) \quad \forall\, i \notin S.$$

Individual rationality and core stability The *individual rationality* constraint (Nash, 1953), or Nash solution, imposes a condition on stability according to which no player

[10] Note that this is analog to the subadditivity assumption for a cost-sharing game.

[11] The notion of internal stability has been extended by Eyckmans and Finus (2009) to the potentially internally stable coalition, which reads as follows: $\hat{x}_i(S) \leq \sum_{i \in S} c_i(S \setminus \{i\})$.

can be better off by deviating from the assigned strategy with constituting a singleton coalition, which can be formalized by

$$\hat{x}_i(S) \leq c_i(\{i\}) \quad \forall\, i \in S.$$

For the remainder, it is assumed that all individual rational allocations are comprised in the set $I(v)$:

$$I(v) = \{\hat{x} \in \mathbb{R}^n : \hat{x}_i(S) \leq c_i(\{i\}) \quad \forall\, i \in S\}$$

The individual rationality property is also implied by the concept of *core stability* (Chander and Tulkens, 1995). Yet, whereas individual rationality and internal/external stability evaluates the stability of coalitions of any cardinality, the concept of the core looks in particular at the stability of the grand coalition. The core aims at finding the vector $y \in \mathbb{R}^n$, the distribution of the value of a coalition with y_i being the allocation towards player i, which fulfills the characteristics of *efficiency* and *coalitional rationality* (see Gillies, 1959). For efficiency, the total gain of a respective coalition must be distributed among all players, which can be formalized by

$$\sum_{i \in N} y_i = v(N).$$

Concerning coalitional rationality, the sum of gains of members of a coalition must not be smaller than the value of the coalition

$$\sum_{i \in S} y_i \geq v(S) \quad \forall S \subseteq N.$$

Hence, the set of all core stable allocations is defined as

$$C(v) = \{y \in \mathbb{R}^n : \sum_{i \in N} y_i = v(N) \quad and \quad \sum_{i \in S} y_i \geq v(S) \quad \forall\, S \subseteq N\}.$$

2.2.2.2 Allocation concepts

TU games include the possibility of transfer payments where the exact design of transfers can impose a higher degree of fairness on coalitions. There exists a big strand of literature that focuses on allocation concepts for gain-sharing. These concepts assign a unique allocation vector $x_i^* \in \mathbb{R}$ to each game.

Existing methods are based on different views on fairness. One strand looks at the fair selection from the subset of cores $C(v)$ and is represented by, for example, the *core cen-*

ter (e.g., González-Díaz and Sánchez-Rodríguez, 2007) and the *least core*. Alternatively, concepts can be based on the power or contribution of individual players. Here, very basic methods propose an equal or production-dependent distribution. More elaborate mechanisms, like the *kernel* (see Davis and Maschler, 1965), *Shapley value*, and *nucleolus*, are based on game theoretical considerations.[12] Within this analysis the least core, Shapley value, and nucleolus will be used to elaborate on the fair allocation of cost.

Least core The concept of the least core x_i^{LC} was introduced by Maschler et al. (1979). It is the cost allocation that minimizes the maximum satisfaction ε for any coalition. Thus, it is assumed to be the cost allocation that players object the least (Schulz and Uhan, 2013). The implementation in this chapter is taken from Drechsel and Kimms (2010) and can be described by the following linear program:

$$\min_{x_i^{LC}} \quad \varepsilon \tag{2.1}$$

subject to:

$$\sum_{i \in N} x_i^{LC} = \hat{x}_i(N) \tag{2.2}$$

$$\sum_{i \in S} x_i^{LC} \leq \sum_{i \in S} \hat{x}_i(S) + \varepsilon \quad \forall S \subset N,\ S \neq \emptyset \tag{2.3}$$

Shapely value In the field of game theoretical approaches, the average contribution of each player to the formation of the coalition underlies the formulation of the Shapley value (Shapley, 1953). The average is taken over all possible permutations in which the coalition can be set up. Hence, it can be interpreted as the marginal benefit from one player joining a coalition if all orderings of players are equally likely (Roth and Verrecchia, 1979). The Shapley value can be formalized as

$$x_i^{SHP} = \sum_{S \subset N} \frac{|S|!\ (N - |S| - 1)!}{N!}\ (v(S) - v(S \setminus \{i\})).$$

Nucleolus Finally, the nucleolus is a sharing mechanism that builds on the notion of the "unhappiness" of the coalition, which is measured by the excess of a coalition $\varepsilon(S, x)$ with $\varepsilon(S, x) = v(S) - \sum_{i \in S}(c_i(\{i\}) - \hat{x}_i(S))$ (Schmeidler, 1969). This can be interpreted as the part of the value of a coalition that the members of the coalition cannot appropriate under a given allocation. The values of $\varepsilon(S, x)$ for different coalitions and allocations can then be comprised in the vector $e(x) \in \mathbb{R}^{2^n - 2}$ and sorted in non-increasing order. Hence,

[12] A more extensive overview of gain-sharing mechanisms can be found in, e.g., Tijs and Driessen (1986); Peleg and Sudhölter (2007); Lozano et al. (2013).

the element $\varepsilon_1(x)$ represents the maximal unhappiness from allocation x. This allows for comparing two allocations x and y by applying the following rule: x is preferred to y if it is lexicographic smaller with $\varepsilon(x) \preceq_{lx} \varepsilon(y)$. The nucleolus of the (N, v) game is then characterized by the following set

$$NC(N, v) = \{x \in X(N, v) : \varepsilon(x) \preceq_{lx} \varepsilon(y) \quad \forall y \in X(N, v)\}.$$

The computational implementation the nucleolus in this analysis is based on the approach proposed in Fromen (1997) and Guajardo and Jörnsten (2015). It can be computed by solving the sequence of linear programs outlined in Appendix B.1.

The very general concept of the nucleolus, which is based on the total excess, resulted in alternative definitions. Grotte (1970) introduced the *per capita nucleolus* as a relative measure, which looks at the per capita excess and aims at minimizing the per capita dissatisfaction. Its formally defined as[13]

$$\varepsilon^{PC}(S, x) = \frac{v(S) - \sum_{i \in S}(c_i(\{i\}) - \hat{x}_i(S))}{|S|}.$$

Other authors adjusted the concept of the per capita nucleolus to the research design of their analysis (e.g., Lejano and Davos, 1995). The same line of reasoning can be applied to the context of this chapter by introducing a relative measure for the excess that is, however, based on the joint carbon emission reductions of a coalition. For the remainder of the chapter, this measure is called *carbon nucleolus*. Instead of dividing by the cardinality of a coalition $|S|$, the carbon nucleolus uses the total amount of reduced emissions in 2050 (compared to 2015 levels) $\sum_{i \in S}(CO2_i^{2015} - CO2_i^{2050})$. It aims at prioritizing coalitions that contribute high emission reductions and thus minimizes the dissatisfaction per units of emission reductions.

2.2.3 Quantification of costs

This chapter applies the *EU-REGEN model* to quantify the first-best cost distribution $\hat{x}_i(S)$ of the future equilibrium outcome of the European power market under a cooperative, subadditive cost-sharing game for each coalition S.[14] The model minimizes the total discounted system cost with respect to a set of constraints. For this analysis, the system

[13] Note that the concept of the nucleolus was not only developed further towards the per capita nucleolus. Other variants are the propensity to disrupt (Gately, 1974) or its generalized concept, the disruption nucleolus (Littlechild and Vaidya, 1976).

[14] The minimization of overall system cost is regarded as an appropriate solution approach since this chapter aims at comparing the efficient market outcome under different coalitions.

cost of the EU-REGEN equilibrium outcome that arises from capacity investment and electricity generation (among others) in a specific region are interpreted as the costs of a region $\hat{x}_i(S)$ under coalitions S. These regional costs underly the individual gain from cooperation, which is understood as the saving in system cost compared to the case when each region constitutes a singleton coalition $c_i(\{i\})$. Hence, the value of each coalition is approximated by $v(S) = \sum_{i \in S}(c_i(\{i\}) - \hat{x}_i(S))$.

The EU-REGEN model The EU-REGEN model (see Chapter 1) is a long-term dispatch and investment model for the European power sector.[15] The model generates quantitative scenarios that represent a cost-effective and consistent decarbonization path for the European power market towards 2050 for regions i, time periods t, and intra-annual time steps s.[16] The linear, deterministic optimization model minimizes the total discounted system cost c^{tot} that comprise investment cost for generation capacity $c^{\mathrm{gc}}_{i,t}$, transmission capacity $c^{\mathrm{tc}}_{i,t}$,[17] cost from generation operation $c^{\mathrm{vc}}_{i,t}$,[18] maintenance cost for generation capacity $c^{\mathrm{fom}}_{i,t}$, and operation and maintenance cost for transmission $c^{\mathrm{tvo}}_{i,t}$ and $c^{\mathrm{tfm}}_{i,t}$. The factor DF_t accounts for the period-specific discounting of cost:

$$c^{tot} = \sum_i c_i^{tot} = \sum_t (c^{\mathrm{gc}}_{i,t} + c^{\mathrm{tc}}_{i,t} + c^{\mathrm{vc}}_{i,t} + c^{\mathrm{fom}}_{i,t} + c^{\mathrm{tvo}}_{i,t} + c^{\mathrm{tfm}}_{i,t}) \cdot \mathrm{DF}_t$$

The model is set-up as a partial equilibrium model that assumes complete markets with perfect information. The main equilibrium constraint is that the market clears in each time segment.[19] Accordingly, the (simplified) market-clearing condition below requires that generation $g_{s,i,t}$, plus electricity imports $im_{s,ii,i,t}$, less electricity exports $ex_{s,i,ii,t}$ has to meet demand $\mathrm{D}_{s,i,t}$.

$$g_{s,i,t} + \sum_{ii} im_{s,ii,i,t} - \sum_{ii} ex_{s,i,ii,t} \geq \mathrm{D}_{s,i,t} \qquad \forall s \in \mathcal{S}, i \in \mathcal{I}, t \in \mathcal{T}$$

---

[15] The notation in this chapter has been adjusted, compared to Chapter 1, to be consistent with Section 2.2.

[16] Note that the presentation of the EU-REGEN model in this chapter abstracts from the existence of different generation technologies and their vintages.

[17] The cost that occur in one region from investing in one additional unit of transmission capacity only represent the investment cost for one direction. The neighboring region must undertake the same investment separately to be able to export. This assumption tries to guarantee consistency with empirical estimates for upper bounds on transmission capacity investments.

[18] The variable generation cost do not comprise the cost for emission certificates. This is based on the assumption that revenues from the auctioning of certificates are distributed in proportion to emissions as it is currently done in the EU ETS (EC, 2017).

[19] The version of the EU-REGEN model used in this chapter does not allow for the endogenous adjustment of demand, for example, by setting a short- or long-run price-elasticity of demand (see Chapter 3 for an example).

Derivation of cost allocations by coalition To elaborate on the impact of considerations of fairness on the market equilibrium and thus derive the first-best cost allocation $\hat{x}_i(S)$ for any given coalition S, this chapter analyzes the equilibrium market outcome under perfect information for a wide number of coalitions. The solution under perfect information is found by solving the cost-minimization problem of the EU-REGEN model for all decision variables simultaneously. Here, transmission capacity investment, generation capacity additions, and dispatch are optimized. Depending on the coalition S under scrutiny, different carbon market constraints are applied. This solution approach is solved for two groups of coalitions:

Concerning the first one, the *first-best scenario* applies a market-wide carbon budget by assuming full cooperation and is interpreted as the grand coalition. Meaning, all regions share a common (time period-specific) carbon budget B_t. Hence, to solve the EU-REGEN model for the grand coalition, the following carbon market constraint is added to the program:

$$\sum_{s,i} g_{s,i,t} \cdot CO2 \leq B_t \quad \forall i \in N, t \in \mathcal{T}$$

with $CO2$ being the average emission factor. Of course, the grand coalition is closely related to the existing EU Emissions Trading System (EU ETS). Here, all participating countries try to reach a joint emission budget.[20] The EU ETS considers all CO_2, N_2O, and Perfluorocarbons (PFCs) emissions from more than 10 sectors of the economy.[21] As with the grand coalition in this analysis, the rationale of the EU ETS is about market participants that coordinate their abatement efforts (by trading emission allowances) to use abatement sources in the ascending order with respect to their marginal abatement cost.

The quantification of the market-wide carbon budget B_t is taken from the energy and climate policies set by the EC. These targets indicate a 40% and 80% (compared to 1990 levels) reduction of economy-wide GHG emissions by 2030 and 2050, respectively. This chapter uses the European Commission's impact assessment on the "[...] policy framework for climate and energy in the period from 2020 up to 2030" (EC, 2014) for the translation into a power sector-specific target. According to this assessment, the level of CO_2 emissions has to reach a 56% reduction by 2030 and a 98% decrease of

[20] The EU ETS comprises the countries of EU28, Iceland, Liechtenstein, and Norway.

[21] The current version of the EU ETS comprises the power and heat generation, oil refineries, steel works and production of iron, aluminum, metals, cement, lime, glass, ceramics, pulp, paper, cardboard, acids, bulk organic chemicals, and civil aviation sector.

emissions by 2050.[22] Furthermore, the EC's assessment assumes that annual electricity generation in 2050 amounts to 5,050 TWh. For the time-steps in between, this chapter assumes a linearly decreasing CO_2 emission budget and increasing electricity demand. The framework in this chapter assumes no energy and climate policy apart from CO_2 prices through CO_2 emission control.

The second group of coalitions comprises each possible coalition $S \subset N$. Based on Section 2.2 and the framework of the EU-REGEN model with $n = 13$ model regions, this results in $2^n - 1 - n = 8,178$ possible coalitions between regions.[23] For this group of coalitions, shared carbon budgets are assumed for regions constituting a coalition $i \in S$. Each region outside the coalition $i \notin S$ is subject to its own carbon budget.[24] These regional carbon budgets $B_{i,t}$ assume a 98% reduction target for each region by 2050. The shared carbon budget for coalitions is the sum of regional carbon budgets $B_{i,t}$ for regions in a coalition. To solve the EU-REGEN model for this group of coalitions, the following two carbon market constraints are included in the program

$$\sum_{s,i} g_{s,i,t} \cdot CO2 \leq \sum_{i} B_{i,t} \quad \forall i \in S, t \in \mathcal{T},$$

$$\sum_{s} g_{s,i,t} \cdot CO2 \leq B_{i,t} \quad \forall i \notin S, t \in \mathcal{T}.$$

Adjustment of cost allocations To fully capture the incentives for electricity exchange, the regional system costs have to be adjusted for electricity exports and imports. Hence, total regional system costs, obtained from solving the linear program of the EU-REGEN model, are adjusted for the value of these quantities. Total regional system cost c_i^{tot} are understood as the sum of discounted cost that arise from capacity investment, electricity generation, and distribution in a certain region. Yet, to consider the benefits of trade, cost from electricity generation should be assigned to the region that actually consumes the generated quantities. The final total regional system cost $\hat{x}_i$ for a respective coalition are the initial system cost c_i^{tot} adjusted for the value of imported and exported quantities and can be written as

$$\hat{x}_i = c_i^{tot} + \sum_{s,ii,t} (im_{s,ii,i,t} \cdot p_{s,ii,t}^{im} - ex_{s,i,ii,t} \cdot p_{s,i,t}^{ex}) \cdot \mathrm{DF}_t.$$

[22] The carbon price resulting from this constraint represent only the marginal abatement cost in the power market.

[23] Note that this number also includes the grand coalition, which falls under the first group of coalitions.

[24] This means that regions outside the coalition cannot utilize geographic differences in marginal abatement cost.

The market-clearing prices in exporting and importing regions, $p^{ex}_{s,i,t}$ and $p^{im}_{s,ii,t}$, are derived from the dual variable of the regional market-clearing constraints.

Note again that the cost for the case of singleton coalitions only $c_i(\{i\})$ are obtained by assuming that all regions $i \in N$ are subject to an own carbon budget. Moreover, the resulting first-best cost allocations $\hat{x}_i(S)$ are assumed to be the cost that members of a coalition $i \in S$ incur if joining the coalition S under scrutiny. Both, $c_i(\{i\})$ and $\hat{x}_i(S)$, will be analyzed in the subsequent Section 2.3.

2.3 Results

The presentation of results starts with characterizing the underlying fist-best cost distribution, results on the stability and fairness of allocations and, finally, an evaluation of these allocations. This is followed by a comparison of the market outcome under the grand coalition and singleton coalitions only.

2.3.1 The cost-sharing game

Characterization of costs The first-best cost distribution of this cost-sharing (cooperative) game is quantified by obtaining the total regional system cost from the EU-REGEN model for all $2^n - (n-1)$ scenarios.

The value of forming the *grand coalition* N shows to be a € 69 billion reduction in total discounted system cost (until 2050) compared to the case of singleton coalitions only. This represents a 4% reduction. 73% of this reduction goes to capital cost and the remaining 27% to operational cost. These values equal the share of capital and operational cost, respectively, in total cost in the case of *singleton coalitions* $\{i\}$ only. Hence, cooperation equally impacts both cost types.

Yet, the value of N to each individual region is highly heterogeneous. It ranges from a € 20 billion (11%) cost decrease in the case of South Germany to a € 9 billion (4%) increase for the North-West of Eastern Europe. The different directions of changes reveal that, from the perspective of single regions, it is not rational to enter N. Table 2.1 shows the cost allocation for $\{i\}$ and N, as well as the relative change between both for each model region (Δ).

The change in regional system cost, when moving from $\{i\}$ to N, can then be explained by changes in the cost structure of the technology-mix. In the case of Scandinavia, higher investment in capital-intensive RES substitutes investment in gas power, which is subject to high fuel cost. Due to the high penetration level of variable RES, the marginal generator in the Scandinavian market is a RES technology with low marginal cost for most time segments. Hence, exported quantities are valued at low prices and do not fully recover the investment cost. Moreover, imported quantities from neighboring regions compensate for the intermittency of RES, which are hence mostly valued at the high marginal cost of flexible gas power.

A first approach towards fair cost-sharing is the *marginal contribution* v_i of a region to N. This can be calculated by contrasting the value of the grand coalition $v(N)$ with the value of a coalition that comprises all regions except for the region of interest, which can be formulated as $v_i = v(N) - v(N \setminus \{i\})$. Results are depicted in Table 2.1. Values indicate that the contribution of all regions is in the same range. However, Britain, Iberia, and South-East Eastern Europe show to have a slightly increased value to N.

Table 2.1: Characterization of cost-sharing game and stable cost distributions [€ billion]

	$C_i(\{i\})$	$\hat{x}_i(N)$	Δ	v_i	$\hat{x}_i(s^R)$	$\hat{x}_i(s^{IS})$	$\hat{x}_i(s^{ES})$
Britain	260	257	−0.01	40	260	258	260
France	293	286	−0.03	35	293	293	293
Benelux	140	125	−0.11	38	140	140	128
Germany-N	149	146	−0.02	34	149	149	147
Germany-S	196	176	−0.11	37	196	196	176
Scandinavia	70	71	+0.01	39	70	70	77
Iberia	290	274	−0.06	42	279	290	275
Alpine	39	31	−0.02	35	39	39	39
Italy	233	225	−0.03	35	233	225	227
Eastern Europe-NW	210	219	+0.04	38	210	210	222
Eastern Europe-NE	13	14	+0.12	38	13	13	14
Eastern Europe-SW	44	45	+0.04	35	44	44	44
Eastern Europe-SE	94	94	−0.01	40	94	93	95

The small difference between the individual values of each region can also be obtained from looking at the value of a coalition as a function of its cardinality. Figure B.1 (see Appendix B.2) shows the maximum and minimum saving (in total system cost) for all coalition cardinalities, which is the number of members. The conclusion from the previous paragraph is verified by the minor difference in the maximum and minimum coalition value for coalitions of cardinality $|N| = 12$. Furthermore, it can be seen that coalitions with a cardinality ranging from 4 to 9 are subject to greater differences between minimum and maximum value. Consequently, the composition of coalitions matters the most for medium size cooperations.

Stability of coalitions The concepts for identifying stable coalitions were introduced in Section 2.2.2.1. In the following, stability will be analyzed based on the *core*, *individual rationality*, and *internal and external stability*.

Testing the first-best cost allocation of the grand coalition $\hat{x}_i(N)$ with respect to the *core*, reveals that the allocation is not core-stable. There are 946 coalitions of smaller size whose members would be confronted with lower cost if they form. Thus, the grand coalition N cannot be reached without the implementation of transfers.

Now solely focusing on the *individual rationality* constraint, or Nash solution, aims at identifying individual disincentives for cooperation. Results show that only 15 coalitions (out of $8,178$) fulfill the individual rationality constraint. The set of coalitions comprises only small-sized coalitions with a maximum cardinality of 4 coalition members. Consequently, the grand coalition cannot be reached under the stability criteria of individual rationality. The coalition with the highest value s^R, out of these 15, comprises the following regions: {Britain, Iberia}. The coalition s^R leads to a cost reduction of € 11 billion. This represents 16% of the gains of N. The cost distribution of s^R is shown in Table 2.1.

Finally, testing the coalitions in this cost-sharing game with respect to *internal and external stability* further indicates the strong impact of a stability criteria. Concerning internal stability, few coalitions (8 out of $8,178$) fulfill this criteria. Again, only small-sized coalitions with up to 4 coalition members pass the test. The internal stable coalition with the highest value, s^{IS} (see Table 2.1), saves € 10.8 billion, which accounts for 16% of the gains of N. The coalition comprises {Britain, France, Italy, South East Eastern Europe}. The external stability criteria is met by 442 coalitions. By definition of the concept, this excludes the grand coalition. Yet, the set of external stable coalitions comprises coalitions with a cardinality of up to 12. For this criteria, the external stable coalition with the highest reduction in system cost, s^{ES} (see Table 2.1), has a value of € 34.2 billion (49% of $v(N)$) and consists of all regions except for France and South-West Eastern Europe. However, applying both criteria reveals that none of the coalitions are internally and externally stable at the same time. As indicated by Bréchet et al. (2011), the result that no or only small-sized coalitions are internally and externally stable is in line with the theoretical findings on internal and external stability in Carraro and Siniscalco (1993) and Barrett (1994).

It is important to emphasize that the concepts of core and internal/external stability build on different views on stability. Whereas the core assumes that the coalition under scrutiny does not form at all if one or multiple players deviate, the internal/external stability concept implies that coalitions form nonetheless (Bréchet et al., 2011). Furthermore, this paragraph revealed that under all concepts of stability (in this chapter) the grand coalition cannot form. For the concepts looking at all coalitions $S \subseteq N$, the individual rationality concept reveals that, if regions act solely rational, at most 16% of the full gains of cooperation can be reached. According to internal and external stability, no coalition is stable. Consequently, only small efficiency improvements can be realized in the absence of transfer payments, which will be analyzed in the subsequent paragraph.

Fair cost-sharing Section 2.2.2.2 introduced concepts for fair cost-sharing under the assumption of a TU game. In the following, results from the application of the *least core*, *Shapley value*, *nucleolus*, and *carbon nucleolus* will be discussed.

Fair cost-sharing based on the *least core* x_i^{LC} builds on the notion of coalitional satisfaction. The values for the least core are shown in Table 2.2. However, the solution to the linear program is not unique. Hence, it should not be interpreted as an optimal cost allocation and will thus be neglected for the remainder of this chapter.

In terms of the group of unique cost allocations, the *Shapley value* builds on the notion of fairness only. Yet, by definition, the *nucleolus* combines the underlying fairness concept with stability. The *carbon nucleolus* goes one step further and considers the absolute emission reduction by coalition for a fair and stable cost distribution. The respective cost allocations x_i^{SHP}, x_i^{NUC}, and x_i^{CNUC} are again displayed in Table 2.2.

This paragraph shows cost allocations based on the least core, Shapley value, nucleolus, and carbon nucleolus. Though, the absolute values of these allocations offer little insight for an evaluation and comparison of these concepts. Thus, the following paragraph analyzes the general implications of the underlying methods with respect to robustness against cost changes, non-bindingness of commitments, and core stability.

Table 2.2: Cost allocations [€ billion]

	x_i^{LC}	x_i^{SHP}	x_i^{NUC}	x_i^{CNUC}
Britain	252	249	251	250
France	290	294	290	292
Benelux	135	134	135	136
Germany-N	146	149	146	142
Germany-S	188	189	189	190
Scandinavia	65	64	65	67
Iberia	282	277	282	281
Alpine	37	38	37	39
Italy	230	232	230	230
Eastern Europe-NW	204	204	204	200
Eastern Europe-NE	6	7	5	9
Eastern Europe-SW	40	42	41	42
Eastern Europe-SE	88	84	88	85

Evaluation of allocations Investment decisions in the power market have long-run implications for system cost and generation potentials. While economic agents base their contemporary decisions on information available at the time, future cost might deviate from these preconceived paths. To assess whether allocations (under different coalitions) are robust with respect to future cost changes, this chapter takes a look at the *monotonicity property* (Young et al., 1979). In this context, the monotonicity property is understood as the change of a cost allocation with a change of the worth of a coalition $v(S)$. Thus, it is another major criterion for fair cost-sharing. In the field of cooperative game theory, it can be differentiated between *coalitional monotonicity*, *weak coalitional monotonicity*, and *aggregate monotonicity* (González-Díaz and Sánchez-Rodríguez, 2007). A cost allocation rule satisfies coalitional monotonicity if for an increase in total cost from $v(S)$ to $v(S)'$ each member suffers higher cost and vice versa, which can be written as

$$x_i < x_i^{'} \; \forall \; i \in S.$$

Weak coalitional monotonicity means that the same applies to the members of a coalition on the aggregate:

$$\sum_{i \in S} x_i < \sum_{i \in S} x_i^{'}$$

Finally, a method satisfies aggregate monotonicity if the same holds for all players of the game on the aggregate:

$$\sum_{i \in N} x_i < \sum_{i \in N} x_i^{'}$$

Concerning the nucleolus, Zhou (1991) showed that it satisfies weak coalitional monotonicity. The Shapley value is the only strongly coalitional monotonic allocation among the methods in this chapter (Young, 1985). At last, Grotte (1970) verified the coalitional monotonicity of the per capita nucleolus. Since the carbon nucleolus is an analog concept, it satisfies this property as well. Table 2.3 summarizes the monotonic property of allocation methods.

In general, it is difficult to make the commitment to the grand coalition N binding. Under this assumption, an allocation x_i^* also has to be evaluated with respect to all strict subsets of N. Meaning, the excess of a permutation under $S \subseteq N$ determines its quality. The *coalitional satisfaction* $F(S)$ under an allocation captures this property. It is defined as the excess of allocated cost x_i^* of players from N over the total cost if coalition S acts independently and can be written as (Lozano et al., 2013)

$$F(S) = \sum_{i \in S} (x_i(S) - x_i^*) \quad \forall \; S \neq \varnothing, \; S \subseteq N.$$

Taking the mean over all coalitions S results then in the average satisfaction F^{AV}:

$$F^{AV} = \frac{\sum_S F(S)}{|S|}$$

The average coalitional satisfaction values F^{AV} for all three methods are shown in Table 2.3. However, the absolute values for F^{AV} should not be interpreted directly. The minor difference between all three methods shows that none of them is superior concerning that criterion.

Section 2.2.2.1 introduced *core stability*, which implies individual rationality, as one criterion for stability of coalitions. Since it captures individual incentives for cooperation, it should also be a criterion for a general evaluation of cost-sharing methods. The nucleolus and carbon nucleolus satisfy the individual rationality criterion by construction. Testing the Shapley value for this criterion reveals that it is not in the core.

Table 2.3: Overview of evaluation of allocations

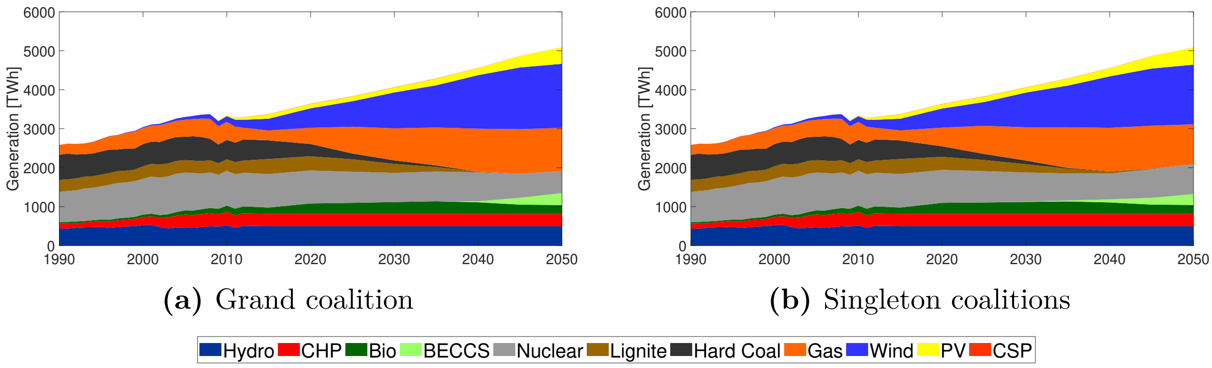
	Monoton.	F^{AV}	Core Stability
Shapley	Strong coal.	€ 18.2 B	No
Nucleolus	Weak coal.	€ 18.3 B	Yes
Carbon Nucleolus	Coal.	€ 18.3 B	Yes

Table 2.3 summarizes the results for all three evaluation criteria. Since the average coalitional satisfaction shows little differences between methods, an overall comparison should be based on the monotonicity and individual rationality property. A positive characteristic of the Shapley value is its strong coalitional monotonicity property. At the same time, the nucleolus and carbon nucleolus proves to exhibit a core stable allocation. Consequently, choosing an allocation method would mean balancing robustness against cost changes and core stability and, thus, individual rationality.

2.3.2 Comparison of market outcomes

The previous Section 2.3.1 focused on the general differences within the set of all possible coalitions. In the following, this chapter will add to this by analyzing the differences between the two most extreme cases, *full cooperation* under N and *no cooperation* under singleton coalitions $\{i\}$.

Generation path The development of the future generation path under a 98% CO_2 reduction target and full cooperation is depicted in Figure 2.1a. Accordingly, wind power is the dominating technology for the EU decarbonization path. Its generation increases more than fivefold until 2050. The attractiveness of wind power can be explained by an expected reduction of investment costs, increasing availability factors, and its positive correlation with load.[25] The latter reflects the seasonal correlation of its availability factors with demand. Both, maximum generation from wind power and demand peak, appear during winter times. Moreover, the bulk of generation is from onshore capacity. Generation from offshore installations proves to be hardly economically viable with its accumulated annual generation constantly staying below 40 TWh.



(a) Grand coalition

(b) Singleton coalitions

Figure 2.1: Long-run generation path under grand coalition and singleton coalitions

The generation-share of variable RES increases over the model horizon from 12% in 2015 to 40% in 2050. Yet, this is mainly driven by wind power. The generation-share of all solar power technologies increases from 5% to 8% in 2050 only. This weak market penetration can be explained in analogy to the attractiveness of wind power. Although, solar power technologies have in general lower availability factors, lower investment costs are not able to compensate for that. Additionally, there is a negative seasonal correlation between generation from solar technologies and demand in most model regions.[26]

In economic terms, the difference in the market penetration between wind and solar power represents each technologies' substitution elasticity with dispatchable technologies. The time-profile of wind power leads to its higher substitution elasticity with dispatchable technologies.

The development of dispatchable technologies in the full cooperation scenario is characterized by investment in gas power technologies and divestment from coal-fired technologies.[27] The former one almost triples its generation-share to 21% and functions as

[25] Increasing availability factors are assumed due to a higher expected conversion-efficiency at lower wind speeds.

[26] Only the Iberian model region shows a positive seasonal correlation between demand and solar irradiation.

[27] The extensive market penetration of gas power has to be interpreted with respect to the framework of the EU-REGEN model. Due to the missing consideration of storage technologies, gas power, as the most flexible generation technology, is a natural complement to intermittent wind power. Consequently, in a framework with detailed modeling of storage, the market penetration of gas power could be lower due to utilization of electricity storage.

complementary technology to wind power. The contribution of coal-fired technologies is monotonically decreasing and falls from 25% in 2015 to 0.05% in 2050.

The increasing generation share of gas-powered technologies in this low CO_2 emission scenario is only feasible due to the market entrance of carbon capture and storage (CCS) with bioenergy (BECCS), which is characterized by a negative carbon intensity. Investments in BECCS arise from 2040 on and allow for a generation-share of 6% in 2050.[28]

The overall generation path in the no cooperation scenario shows little differences (see Figure 2.1b). The generation paths between N and the singleton coalitions $\{i\}$ differ with respect to the utilization of low-carbon generation technologies. Moving from N to $\{i\}$ increases, on the one hand, the generation from nuclear power and PV and reduces the contribution of wind power, gas power, BECCS, and concentrated solar power (CSP), on the other hand. This can be seen in more detail when looking at the regional generation patterns.

The respective development of regional generation paths can be found in Figures B.2, B.3, B.4, and B.5 in Appendix B.3. Under the grand coalition, the quality of wind and solar resources shows to be the main driver for the geographic distribution of wind and solar power generation. This is in contrast to other contributions that emphasize the benefit of a geographic distribution, which utilizes a geographic averaging effect to smooth overall wind power generation (e.g., Huber et al., 2014). The model region Britain becomes dominating in wind power application by reaching an annual generation of 400 TWh by 2050, accounting for approximately 25% of 2050 total wind power generation. Moreover, also France and Scandinavia experience a significant increase in generation from wind power. Generation from solar resources is mainly added in the southern regions, namely Iberia, France, and Italy.[29]

Comparing that to the results for the singleton coalitions, two patterns can be observed. On the one hand, with singleton coalitions, there is a switch from wind power to nuclear power. The generation path for France indicates this development clearly. On the other hand, there is also a geographic shift of generation from gas power. This becomes obvious when comparing Germany and North-Western Eastern Europe in both scenarios.

[28] The carbon intensity of BECCS is negative due to the removal of CO_2 from the atmosphere in the biomass growing phase in combination with the geologic storage of CO_2 emissions from the biomass combustion. The general importance of BECCS in low CO_2 emission scenarios has been emphasized in, e.g., Klein et al. (2014).

[29] The market penetration of solar power in these countries can be explained by regional resource quality, which strongly correlates with latitude.

Capacity investment path The development of the long-run generation path is reflected in capacity investment. Figure 2.2a shows the underlying capacity path for the grand coalition. The strong build-up of solar and, especially, wind power capacity is necessary because of the low substitution elasticity with dispatchable generation technologies. Due to the lower availability factors and intermittency of variable RES, greater amounts of capacity are required to substitute dispatchable and CO_2-emitting generation technologies.

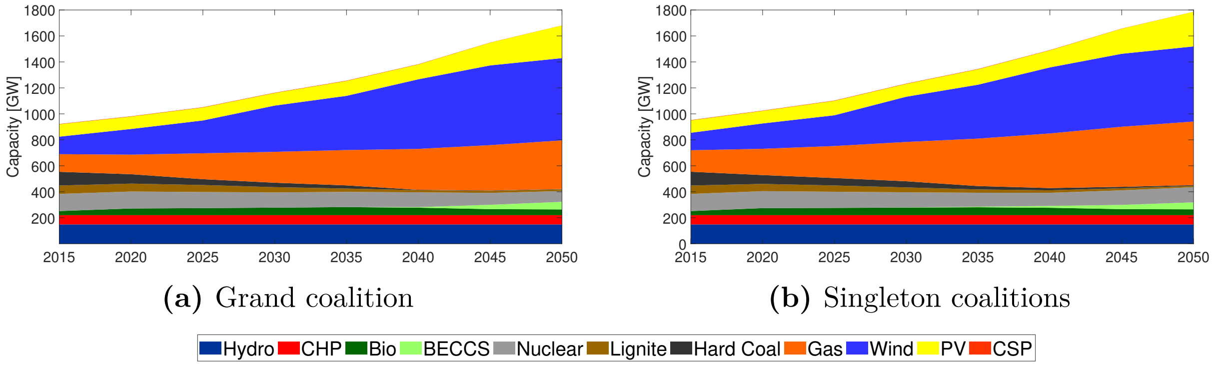


Figure 2.2: Long-run capacity path under grand coalition and singleton coalitions

Furthermore, a look at the timing of solar power investments reveals the importance of its decreasing investment costs. The majority of new capacity is added in the mid- and long-run, where assumed investment costs experience a strong decrease. In terms of technology, only photovoltaic power proofs to be an economically attractive technology. CSP hardly penetrates the market. Meaning, its higher availability factors and flexibility through storage does not compensate for higher investment costs.

Moreover, Figure 2.2a indicates the gradual phase-out of coal-powered technologies. By 2050 only 15 GW of coal power capacity remains active, which corresponds to 9% of the capacity installed in 2015. The stock of nuclear power capacity decreases by one-third.[30]

In contrast to that, the capacity investment path under singleton coalitions (see Figure 2.2b) shows an almost stable capacity level of nuclear power. This goes in hand with a reduction in the wind power capacity. Furthermore, results show that, even though, the generation from gas power is lower in the singleton coalition scenario, the level of installed capacity in 2050 increases. This reveals a lower utilization of the capacity and, hence, a loss in economic efficiency.

[30] The gradual decrease of the nuclear power capacity is driven by the exogenous technical lifetime of generation technologies (60 years for nuclear power) and the absence of new investments in the cost-efficient market outcome.

Prices In addition to the market-clearing condition, the carbon budget is another main equilibrium constraint in the context of this analysis. The duel variable of the market-clearing and carbon budget constraint provides insight in the energy-only prices and marginal abatement cost, respectively. Table 2.4 shows the development of both prices.

The relative market-wide energy-only price (compared to the level of 2015) experiences an increase in, mainly, the mid-run (until 2040) (see Table 2.4). Prices rise to 1.14 in 2030 and balance out around 1.30 by the end of the model horizon. This can be interpreted as a 30% price increase compared to 2015 due to the low-emission target in this chapter. The underlying regional energy-only prices are depicted in Table B.1 (see Appendix B.3), which indicate a heterogeneous development of regional energy-only prices. Relative regional prices by 2030 range from a decrease to 0.99 in the case of Britain to an increase to 1.38 in South-East Eastern Europe. For 2050, prices in Britain are at a level of 1.13 and the South-East of Eastern Europe reaches a level of 1.44. The differences between regions are, on the one hand, driven by varying growth patterns of future electricity demand and, on the other hand, by regional variable RES availability and quality, among others.

The relative market-wide energy-only price under singleton coalitions is characterized by a lower increase then in the case of the grand coalition (see Table 2.4). Values are at a level of 1.08 by 2030 and reach 1.23 in 2050. Thus, the marginal cost for generating electricity even decrease under no cooperation. Consequently, the economic consequences from singleton coalitions mainly translate into an increase of capacity costs, which is also indicated by the increase of overall generation capacity (see Figures 2.2a and 2.2b). Moreover, the regional energy-only prices (see Table B.2 in Appendix B.3) follow the same pattern as under the grand coalition.

Table 2.4: Relative energy-only (compared to 2015) and CO_2 prices

Grand Coalition	2020	2025	2030	2035	2040	2045	2050
Relative energy-only price	1.05	1.13	1.14	1.18	1.26	1.29	1.30
CO_2 prices [€/tCO_2]	7.4	19.6	24.5	35.6	57	84.5	95.5
Singleton Coalitions	2020	2025	2030	2035	2040	2045	2050
Relative energy-only price	1.04	1.10	1.08	1.14	1.19	1.22	1.23
CO_2 prices [€/tCO_2]	11.8	21.5	28.5	39.8	59.7	84.4	103.5

Note: The market-wide energy-only price is calculated as the generation-weighted average of all regional market-clearing prices.

The marginal abatement cost in the European power market under the grand coalition increase constantly to 24 €/tCO_2 in 2030 and reach 95 €/tCO_2 in 2050. Usually it is assumed that these abatement cost are recovered in the economy. Yet, from the perspective of consumers, there is empirical evidence that emission cost are passed-through to electricity prices (see Fabra and Reguant, 2014; Hintermann, 2016). This would translate into an even stronger increase of energy-only prices.

As pointed out in Section 2.1, non-cooperation leads to regional differences in marginal abatement cost. In the case of singleton coalitions, there is a band of regional abatement costs that varies from 39 €/tCO_2 to 162 €/tCO_2 in 2050. A region like Alpine, that does not have access to low abatement cost through high quality RES, ends up with marginal abatement cost of 162 €/tCO_2. On the contrary, the wind resource rich region Scandinavia reaches a level of 69 €/tCO_2 by 2050. Finally, the average marginal abatement cost in this scenario reach a level of 104 €/tCO_2 by the model horizon and, hence, further indicate the loss in economic efficiency from singleton coalitions.[31]

Geographic distribution of CO_2 abatement The access to CO_2 abatement at low marginal cost, for example, variable RES, is one of the main drivers for differences in regional CO_2 emission reductions. Neglecting regional differences in abatement costs and not utilizing those would mean, in this scenario, that each region reduces its CO_2 emissions by 98%. Yet, the cost-efficient partial equilibrium from the EU-REGEN model proves the regional emission-reduction paths shown in Table 2.5 to be optimal.

Table 2.5: Development of regional CO_2 emissions (compared to 1990)

	2015	2020	2025	2030	2035	2040	2045	2050
Britain	0.72	0.46	0.23	0.19	0.20	0.21	0.20	0.16
France	0.71	0.38	0.28	0.37	0.51	0.43	0.38	−0.09
Benelux	0.59	0.61	0.60	0.70	0.73	0.76	0.73	0.74
Germany-N	0.78	0.71	0.58	0.51	0.36	0.14	0.08	0.06
Germany-S	0.79	0.74	1.20	1.13	1.14	1.20	0.95	0.69
Scandinavia	0.41	0.31	0.20	0.18	0.20	0.13	−0.44	−1.02
Iberia	1.18	1.04	0.98	0.95	0.86	0.54	0.30	0.02
Alpine	0.85	0.81	0.72	0.80	0.97	1.18	1.04	0.93
Italy	0.68	0.69	0.63	0.50	0.37	0.27	0.18	0.06
Eastern Europe-NW	0.69	0.62	0.53	0.33	0.14	0.05	−0.04	−0.08
Eastern Europe-NE	0.36	0.29	0.11	0.04	0.01	0.00	−0.08	−0.16
Eastern Europe-SW	0.84	0.67	0.46	0.35	0.04	0.00	−0.27	−0.41
Eastern Europe-SE	0.86	0.91	0.72	0.43	0.17	0.03	−0.13	−0.20

Note: CO_2 emission values are normalized to 1990 levels.

The presented values show that Iberia is the only region for which it is optimal to reach a 2050 level that is equal to the market-wide target as it reaches an emission level of 2% compared to 1990 levels. All other regions either over- or under-fulfill the 98% reduction target. Scandinavia, France, and the Eastern European regions even reach negative

[31] The abatement cost are calculated as the emission-weighted average of all regional marginal abatement costs.

emission levels.[32] Especially Scandinavia shows a high reduction of relative emissions by reaching with −1.02 a negative emission level of the same magnitude as the 1990 positive emission level. This is, on the one hand, driven by the strong market penetration of variable RES and, on the other hand, by the application of BECCS. The regions with the highest remaining emission levels are Benelux, South Germany, and Alpine.

By design of the singleton coalitions scenario with a carbon budget for each region, regional emissions follow the assumed 98% reduction target. Hence, emissions in each region end up at a level of 2% compared to 1990 levels.

2.4 Discussion and conclusion

In this chapter, two scenario groups were analyzed. First, cooperative game theory was applied to investigate effects of cooperation. The total system cost under the *grand coalition* decrease by 4% compared to the case with singleton coalitions. Looking at the stability of all possible coalitions reveals that only small-sized cooperations pass the test for individual rationality and none fulfills the criteria of internal and external stability at the same time. Finally, the identification of fair cost allocations indicates a trade-off between considering robustness against cost changes and individual rationality.

Second, in case of the grand coalition (the first-best), the interplay between wind power, gas power, and BECCS is shown to be the cost-effective equilibrium for the decarbonization of Europe's power sector. Onshore wind power shows to be the most crucial generation technology with a generation-share of over 30% by 2050. The flexible dispatch pattern of gas power backs up this strong market penetration. Moreover, the market-wide marginal abatement costs in 2050 end up at 95 €/tCO_2. Under *singleton coalitions*, the generation and capacity investment paths show a greater contribution of nuclear power, which substitutes generation from wind power. Hence, this analysis finds different technology lock-ins under the grand coalition and singleton coalitions, respectively. For the regional marginal abatement costs, the average of these costs reaches a level of 104 €/tCO_2 by 2050 under singleton coalitions.

Finding the equilibrium market outcome by means of a bottom-up power market model offers great insights into the underlying investments and capacity utilization. Yet, using such a model for analyzing coalitions and also the concepts of cooperative game theory themselves, implies a variety of limitations. Three of these issues are addressed in the

[32] Negative emissions arise from the application of BECCS.

following.[33] First, results show that differences in the main variables between the grand coalition N and the singleton coalition $\{i\}$ are minor. With respect to that, it is important to emphasize the low-emission path that is underlying this analysis. The system-wide 98% reduction target is a tight constraint that deeply limits the solution space. Conducting the same analysis with an 80% reduction target instead, validates the great impact of the tighter reduction target. With an 80% reduction target, the total system cost under $\{i\}$ increases by 7% (compared to 4% in Section 2.3.1). Yet, it is not clear whether that can be interpreted, such that a tight climate target is one way to limit inefficient behavior of individual countries or regions. This should be subject to further analysis. Second, the question of the explanatory power of total system cost is closely related to that. The analysis in this chapter shows that even under the grand coalition N and singleton coalitions $\{i\}$, the difference in total system cost is minor. This has been emphasized by, for example, Trutnevyte (2016) and DeCarolis (2011). They show that a great number of near-optimal scenarios can represent observed market developments as well. Furthermore, it is shown in the literature, that equilibria with similar total system cost can represent very different transition paths. Insights from this analysis indicate that the marginal abatement costs are a more suitable indicator. Yet, the adjustment of total cost for imported and exported quantities in this chapter already tries to address this point of criticism. Third, one general weakness of this approach is the one-dimensionality of coalitions. The framework assumes that while one coalition is formed, all the other regions constitute singleton coalitions. Yet, this leaves out the possibility of alternative cooperations that could be formed in parallel. The main reason for sticking to this one-dimensional perspective is computational capacity. The setting in this chapter requires $8,178$ model runs to quantify the full cost-space for the cost-sharing (cooperative) game. Looking into a second round of coalition formation would not allow for quantifying the cost-sharing game anymore.

The analysis in this chapter provides general implications with respect to the *EU ETS*. The research design in this study allows to gain insight in the direction of potential transfer payments to reach the grand coalition and the cost-effective equilibrium. However, this raises the question of how to implement a system of transfer payments and which institutions would be required. As mentioned in Section 2.2.3, the concept of cooperation in this chapter exhibits a close relationship to the one of the EU ETS. With respect to the EU ETS, one channel of reallocation is the sharing of auctioning revenues. This reallocation scheme should consider the economic rationality of single countries as discussed in this chapter. Looking at the data for the allocation of revenues from the auctioning of

[33] The topics addressed in this section should be understood as a selection of critical issues. Of course, there are further issues connected to the methodology in this chapter.

emission allowances for the years 2013–2015 shows that national revenues are distributed (roughly) in proportion to the amount of national emissions (for auctioned allowances). Thus, Germany received 22% of revenues, followed by Italy and the United Kingdom with 12% each. Moreover, the available data from EC (2017) shows to which extent countries spend revenues on international uses related to climate purposes. The cost allocations in Section 2.3.1 revealed that (based on the carbon nucleolus) South Germany, Benelux, Iberia, Alpine, and Italy would be the main contributors to a transfer scheme. So, these countries should also have significant spendings (of allocations of revenues) for international purposes.[34] The observed numbers show that the two Iberian countries Spain and Portugal dedicate less than one percent to international climate uses. However, Germany allocates 8%, Austria 13%, and Italy 50% of its revenues to international purposes.[35] Another source of transfer in the current EU ETS is the free allocation of allowances for the modernization of electricity generation. For the years 2013–2015, these free allowances were given to Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Lithuania, Poland, and Romania (EEA, 2018). According to the proposed cost allocation (based on the carbon nucleolus) all Eastern European regions would receive transfers. Hence, the existing allocation of transfers through free allowances for the modernization of electricity generation and the observed reallocation of auctioning revenues is mainly in line with the results obtained from the analysis in this chapter.

However, the present analysis addresses only the European power sector, which is in contrast to the more than 10 sectors of the EU ETS. Since it can be assumed that more and more ETS sectors will move from freely allocated allowances to auctioning in the future, a similar analysis, that comprise all of these sectors, should be conducted to fully capture the implications for the EU ETS. Related to that, there is also the necessity for analyses that look at alternative ways for setting economic incentives, which could be derived from the literature on international trade agreements. For instance, the concept of foreign direct investments could be used to think of cross-border capacity payments.

Finally, as highlighted in the course of this chapter, the EU already laid the ground for transforming its power sector by setting long-run decarbonization goals. However, it is important to emphasize that the EU has shared competences with its member states and still has to rely on them for the translation of its climate policy goals into actual targets or national legislation. As long as this is the case, the EU should set appropriate incentives such that member states implement targets, which serve the efficient implementation of

[34] Note that these numbers do, unfortunately, not reveal which European country receives these transfers.

[35] Due to incomplete data availability, the share of auctioning revenues that goes to international climate uses cannot be evaluated for the countries of the Benelux region.

goals. Consequently, new EU policies that are currently under way or still to come should include more comprehensive transfer schemes as proposed in this paper.

In general, the EU's *Energy Union* is a first step towards this process. The EC makes the benefits of each member state transparent by highlighting them explicitly.[36] Nonetheless, a clear reallocation scheme remains missing. In 2018, the EU passed new regulation on the governance of its Energy Union and climate action plans. However, also this new piece of legislation lacks explicit transfers, which indicates that accounting for distributive effects of legislation related to the Energy Union is still the exception. Having the results of this chapter in mind, following through with this approach could lead to profound dissatisfaction of single EU member states and thus opposition towards the efficient implementation of a transformation path.

[36] The benefits of the Energy Union for each EU member state are listed under https://ec.europa.eu/commission/publications/benefits-energy-union-country-factsheets.

Chapter 3

Power Markets in Transition: Decarbonization, Energy Efficiency, and Short-Term Demand Response

3.1 Introduction

To keep global warming below 2° C, 195 countries committed to counteract their current trend of CO_2 emissions in the 2015 Paris Agreement. To limit the probability of warming above 2° C, cumulative CO_2 emissions in the period 2000–2050 should not exceed 1,000,000 megatons (Mt), that is, approximately 20,000 Mt each year (Meinshausen et al., 2009). In 2017, just two years after the Paris Agreement, annual carbon emission peaked at 36,790 Mt, which is almost double the approximate annual emission budget and, moreover, means that almost half the 1,000,000 Mt budget has already been emitted. Thus, there is doubt as to whether the temperature target can be met.[1]

One driving factor behind this development is the annual emissions from electricity generation, which increased from 6,300 Mt to 11,700 Mt in the period 1990–2013 (Ang and Su, 2016) and thus accounts for around one-third of total emissions. Electricity demand increased by 94% in the same period and is expected to increase further due to rising household incomes (preference for using electricity), electrification (heating, transportation, power-to-gas), digitization (e.g., cryptocurrencies), and increased use of air-conditioning. To date, the power sector's decarbonization efforts have mainly focused on its supply side. Policymakers introduced cap-and-trade systems (e.g., the European emission trading system (EU ETS)) or initiated support schemes for renewable energies (e.g., feed-in tariffs).

Concerning renewables, their intermittent supply pattern is a challenge to decarbonization. Complementing technologies, that can react to fast changes in the supply of renewables and provide the necessary flexibility on the supply side, are either carbon-emitting (gas power), scarce regarding suitable sites (pumped hydro, biomass), still too expensive (batteries, power-to-gas), or difficult to incentivize (short-term demand response)[2]. Thus, there is an increasingly strong focus on long-term demand response measures such as *energy efficiency*, which reduces the overall electricity demand that has to be satisfied. For example, the International Energy Agency (IEA) calculates that improvements in energy efficiency reduced carbon emissions by 12.5% in the period 2000–2016 (IEA, 2017b, p. 27) and predicts that further improvements will provide 44% (renewables 36%,

[1] Note that even a warming of 2° C comes at enormous cost. Supposing social costs of carbon of 100 US$/t$CO_2$ (see Tol (2011) for a survey and Anthoff and Tol (2013); Nordhaus (2014); Pindyck (2016); van den Bijgaart et al. (2016); Ricke et al. (2018) for estimates that vary between 10 and 805 US$/t$CO_2$) and future emissions of 500,000 Mt, leads to economic costs of US$ 50 trillion, which is 2.5 times the 2017 US GDP.

[2] Smart meters would make short-term demand response feasible, but the actual response is still behaviorally biased.

fuel switching 2%) of the abatement necessary to meet the Paris Agreement targets (IEA, 2018, p. 28).[3]

In this chapter, we develop a framework to integrate short-term demand response and long-term demand response (energy efficiency improvements) in detailed dispatch and investment models of power markets. We implement this framework in the EU-REGEN model to find the welfare maximizing level of investments in energy efficiency, quantify its impact for decarbonizing the European power sector, and elaborate on the role of short-term demand response and its interaction with the supply side.[4] It is well-known that improvements in energy efficiency reduce the price of electricity and thus have a rebound effect, the magnitude of which depends, among others, on the *short-term demand response*; that is, consumers' abilities to adapt their demand in the current period (*demand shedding*) and reschedule demand intertemporally (*demand shifting*).

To account for European decarbonization goals, we implement a carbon constraint of 80% emission reduction in the period 1990–2050. We assume perfectly competitive firms that decide on production and capacity investments in the face of carbon prices. Consumer behavior is reflected by a downward sloping inverse demand function that accounts for demand shedding and shifting. The framework is set up from the perspective of a welfare-maximizing central planner. The central planer can invest in the level of energy efficiency and thus reduce the amount of electricity necessary to provide the same amount of energy services. A performance parameter translates the investments into actual savings. This parameter is assumed to increase over time to account for exogenous technological progress in energy efficiency on the demand side.[5]

We calculate that, under short-term demand response and optimal energy efficiency investments, there will be a need for 180 GW less gas turbine capacity until 2050 compared to a scenario that neglects responsive demand, but 52 GW more solar PV and 28 GW more wind turbines would be installed. Nuclear, lignite, and coal power are hardly affected. Smart devices and tariffs with time-varying prices incentivize consumers to adapt their demand in response to supply scarcity in the short term. This increases system flexibility and thus reduces the general need for flexibility on the supply side, which is

[3] Fuel switching is the change in the emission intensity of fossil fuel-based generation technologies due to switching to fuels with a lower carbon content (either natural gas instead of coal or biomass instead of natural gas) or power plants with a higher conversion efficiency.

[4] The EU-REGEN model is a dynamic partial equilibrium model of the European power market with multiple regions that are linked via transmission lines (see Chapter 1).

[5] Exogenous technological progress on the supply side is covered by technology-specific developments over time.

mainly offered by gas power.[6] Additionally, short-term demand response leads to more (less) consumption when wind and solar power generators have plenty (little) to sell. This reduces the temporal variability of prices, which fosters the competitiveness of solar power but decreases gas power revenues. Wind power benefits less than solar power because its intermittency is less pronounced. For nuclear, lignite, and coal power, less prices variability translates into an intertemporal shifting of profits and thus does not affect their capacity in the long run.

We find that energy efficiency reduces electricity demand by 10% in 2050. In contrast, the EU 2012 energy efficiency directive and its 2016 update set a target of 20% reduction in energy demand by 2020 and a 30% reduction target for 2030. Energy efficiency contributes 11% to the decarbonization of the European power market. Wind turbines, solar PV, and gas power are the chief means of meeting the emission target (intermittent renewables 53%, fuel switching 36%), which is in sharp contrast to IEA (2018). Keeping our framework in mind, other studies seem to overestimate the economic attractiveness of energy efficiency, for two reasons. First, the interplay between short-term demand response and energy efficiency improvements leads to a rebound and thus diminishes the projected savings. However, we calculate that the rebound effect is 9% and hence does not play a crucial role. Second, on the supply side of the market, short-term demand response partly balances the intermittent supply pattern of renewable energies and increases their economic viability.

The literature on energy efficiency is mainly concerned with two phenomena: the *rebound effect* and the *energy efficiency gap*.[7] The rebound effect refers to the loss in energy efficiency savings due to economic response (Gillingham et al., 2016). The energy efficiency gap is understood as an energy efficiency level lower than the socially optimal level (Jaffe and Stavins, 1994). The existence of a rebound effect is widely accepted and has been long discussed in the literature (e.g., Jevons, 1865; Khazzoom, 1980; Lovins, 1988). In our partial equilibrium setting, we capture the effect on energy consumption of improved energy efficiency due to income and substitution effects (direct or *partial equilibrium rebound effect*) and abstract from income and substitution effects on all other goods (indirect or *general equilibrium rebound effect*).[8]

Regarding the energy efficiency gap, Gillingham and Palmer (2014) recently wrote that "[d]espite more than thirty years of research on the energy efficiency gap, the issue of its

[6] Must-run generators such a nuclear, lignite, and coal power are not as flexible as gas power due to ramping times.

[7] See Borenstein (2015); Chan and Gillingham (2015); Lemoine (2016) for theoretical contributions and Greening et al. (2000); Jenkins et al. (2011); Sorrell (2009) for literature reviews.

[8] See Fullerton and Ta (2018); Böhringer et al. (2018) for a more detailed decomposition.

size remains unresolved." Two other publications have shed new light on this issue. Using evidence from an energy efficiency program for 30,000 low-income households, Fowlie et al. (2018) find realized savings at roughly 30% of the projected ones. On the basis of a 100,000-household field experiment, Allcott and Greenstone (2017) estimate savings of 58% in comparison to engineering projections. Moreover, they find no evidence for the informational or behavioral explanations that are often discussed in the literature, and conclude that modeling flaws such as hidden costs, exaggerated energy savings from engineering projections, and consumer heterogeneity contribute to the size of the observed energy efficiency gap.[9]

We use existing estimates for price elasticities to calculate the rebound effect. Regarding the energy efficiency gap, we account for the fact that engineering estimates on the impact of energy efficiency might be wrong. Fowlie et al. (2018) and Allcott and Greenstone (2017) suggest that actual performance might be only half of our default guess. Under such a scenario, the economic attractiveness of substitutes (wind turbines, solar PV, gas power) results in negligible energy efficiency investment.

Stylized, partial equilibrium models of power markets usually assume that consumer's utility maximization leads to a generic downward-sloping demand curve (e.g., Fischer and Newell, 2008; Green and Leautier, 2015). This setting is especially used in the classical peak-load pricing literature (see Crew et al., 1995), where consumers are able to adapt to expected prices (e.g., day-ahead or flat prices) but cannot react after the uncertainty has been resolved (e.g., real-time price) due to the lack of smart meters and suitable tariffs.

Detailed power market models consider the temporal variability of demand either through short-term demand response or exogenously given temporal demand profiles. An example for the latter is the model introduced in Chapter 1. Concerning short-term demand response, Zerrahn and Schill (2015) represent short-term demand response by a system of equations, which limits the amount of demand and number of periods over which demand can be shifted. This approach keeps the problem linear and their objective is to minimize costs.[10] In contrast, Su and Kirschen (2009) and Jonghe et al. (2011) take a welfare-maximizing approach. Su and Kirschen (2009) maximize welfare as the difference between the gross surplus and cost, where gross surplus is approximated by the product of consumers' marginal benefits and the quantity consumed. Jonghe et al. (2011) maximize welfare by using a first-order Taylor linearization of demand and thereby

[9] Note that exaggerated savings lead to higher estimates for the rebound effect and are one explanation for empirical observations of rebound effects above 100%.

[10] See Göransson et al. (2014); Richter (2011) for similar studies.

account for demand shedding, shifting, and the level of energy efficiency, which can be varied exogenously. Even though Jonghe et al. (2011) explore a novel approach, the still exogenous level of energy efficiency and the lack of differentiation between demand for electricity and energy services limit its applicability. We borrow from them to depict demand shedding but develop our own, more intuitive approach for demand shifting and energy efficiency.

Other representations of energy efficiency in detailed partial equilibrium power market models are sparse and limited to cost-minimizing models (see Chapter 4).[11] Like us, Lind et al. (2013) model energy efficiency as an investment option with different cost classes and respective potentials.[12] EPRI (2014) use the US-REGEN model (see Blanford et al., 2014) and integrate, similar to our model, energy efficiency as a separate technology in the market-clearing condition. For subsequent years, the performance of the energy efficiency measure depreciates. In our model, the performance of energy efficiency increases exogenously due to technological progress but the endogenous determined capacity of energy efficiency depreciates. However, we go beyond the approach in EPRI (2014) and additionally consider the current level of energy efficiency and the general interaction of energy efficiency with short-term demand response.

The remainder of the chapter is organized as follows: Section 3.2 describes the model and the underlying optimization problem. Then, in Section 3.3, we develop the framework to implement short-term demand response and energy efficiency improvements in detailed power market models. Section 3.4 describes the calibration and Section 3.5 the results. Section 3.6 close the chapter with discussions and a conclusion.

3.2 The model

Consider a dynamic partial equilibrium model of a multi-region electricity system. Our model comprises firms, consumers, and a central planer. The overall objective is to maximize welfare taking into account the behavior of firms and consumers. The market consists of regions r and consumption sectors i. We consider dispatchable and intermittent technologies j. The time horizon of the model is split into periods t and each period consists of segments s. We use y for production, q for new installed capacity, Q for aggregated capacity, and $C(\cdot)$ is for cost functions. The absolute level of the cost functions varies among regions and their shape depends on the technology j. We use sub-

[11] See Baldini and Trivella (2018) for an approach that emphasizes the technological heterogeneity of energy efficiency measures.

[12] For quantification they use the TIMES-Norway model (see Loulou et al., 2005).

scripts i, j, r, and parentheses $(t), (s,t)$ to denote variables, for example, $y_{jr}(s,t)$ refers to technology type j, region r, segment s, and period t.

At the beginning of each period, firms invest $C_{jr}(q_{jr}(t))$ to install $q_{jr}(t)$. Each technology's capacity has a certain lifetime. Thus, $Q_{jr}(t)$ is reduced by the amount of capacity that reached the end of its lifetime in period t. Holding capacity costs $C_{jr}(Q_{jr}(t))$ and makes it potentially beneficial to take some vintages out of operation before they reached the end of their lifetimes. In each time segment, firms decide on production, $y_{jr}(s,t)$, at private costs $C_{jr}(y_{jr}(s,t))$. Production leads to emissions, denoted by $e_{jr}(s,t)$, and is restricted by available capacity, that is, $y_{jr}(s,t) \leq \alpha_{jr}(s) Q_{jr}(t)$, where $\alpha_{jr}(s)$ is the availability of technology j.

We assume that firms are perfectly competitive and emissions cause environmental damage by burning fossil fuels to generate electricity. Abstracting from any uncertainty and assuming price-responsive consumers, firms obtain zero profits in each period. Additionally, neglecting from dynamic market failures such as R&D spillovers, it is straightforward to show that firms would act efficiently if environmental externalities are perfectly internalized (e.g., Golosov et al., 2014).[13] We abstract from representing policies addressing environmental externalities other than the carbon externality from burning fossil fuels. There are various policy instruments for limiting CO_2 emissions, for example, a carbon tax, direct control instruments to ban certain fossil fuel burning technologies, or certificates to limit emission quantities. We impose a quantity restriction path—$\overline{E}(t)$ denotes the emission target and $E(t) = \sum_r \sum_s \sum_j e_{jr}(s,t)$ is the actual emission level—which leads to an 80% emission reduction in the European power market in 2050.[14] For parsimony, we assume that the resulting certificate price internalizes all damages so that firms act efficiently.

Consumers obtain utility from the consumption of energy services. Energy service demand is denoted by $x_r(s,t)$, the resulting electricity demand by $d_r(s,t)$, and $p_r(s,t)$ is the time-varying wholesale electricity price. We denote by $\epsilon_i^s < 0$ the ability to shed demand[15] in segment s and by $\epsilon_i^{s,s'} \leq 0$ the ability to shift demand from s to s'. Taking this into account and noting that $x_r(s,t) = \sum_i x_{ir}(s,t)$ is the energy service demand of all sectors, consumers maximize their utility by responding to time-varying electricity prices. This leads to the inverse demand function, denoted by $p_r(x_r(s,t))$, so that $\int_0^{x_r(s,t)} p_r(\tilde{x})\, d\tilde{x}$ is the "gross surplus" from consuming energy services. Subtracting costs

[13] Externalities from R&D spillovers would require subsidies (e.g., Acemoglu et al., 2012).

[14] See Chapter 1 for more information on this scenario.

[15] Note that the ability to shed is defined as the percentage change in quantity over the percentage change in price.

of purchasing electricity, yields consumer surplus

$$CS_r(s,t) = \int_0^{x_r(s,t)} p_r(\tilde{x})\, d\tilde{x} - p_r(s,t)\, d_r(s,t)\,. \tag{3.1}$$

Each region can trade electricity with other regions. $IM_{r,r'}(s,t)$ and $EX_{r,r'}(s,t)$ denote the import or export volume, respectively, between two regions r and r'. Then, imports to a specific region r are defined by $IM_r(s,t) := \sum_{r' \neq r} IM_{r,r'}(s,t)$ and exports by $EX_r(s,t) := \sum_{r' \neq r} EX_{r,r'}(s,t)$, where $r' \neq r$ defines a subset of regions that does not contain the specific region r. Net imports are $TR_r(s,t) = IM_r(s,t) - EX_r(s,t)$ and restricted by transmission line capacity. To alleviate this constraint, the central planer invests $C^{tr}_{r,r'}\left(q^{tr}_{r,r'}(t)\right)$ to install transmission line capacity, $q^{tr}_{r,r'}(t)$, between regions r and r'.

The transformation of electricity into energy services is determined by the level of energy efficiency. The central planer invests $C^{ee}_{ir}(q^{ee}_{ir}(t))$ in each region to improve the energy efficiency of sector i by $q^{ee}_{ir}(t)$. The aggregated energy efficiency capacity, $Q^{ee}_{ir}(t)$, depreciates at rate δ^{ee}. Using the introduced investment costs and assuming that all variables are non-negative, we can formulate the central planner's objective as

$$\begin{aligned}
\max_{\mathbf{q},\mathbf{y}} W &= \sum_t \sum_r \left(\sum_s CS_r(s,t) + \sum_j \pi_{jr}(t) - \sum_i C^{ee}_{ir}(\cdot) - \sum_{r' \neq r} C^{tr}_{r,r'}(\cdot) \right) && (3.2)\\
\text{such that } 0 &= \sum_j y_{jr}(s,t) + TR_r(s,t) - d_r(s,t)\,, && (3.3)\\
Q^{tr}_{r,r'}(t) &\geq IM_{r,r'}(s,t)\,, EX_{r,r'}(s,t) && (3.4)\\
0 &\leq \overline{E}(t) - E(t)\,, && (3.5)
\end{aligned}$$

$\pi_{jr}(t)$ denotes technology-specific profits of firms in a specific region. The central planner maximizes welfare as the sum of consumer surplus and producer surplus, minus costs of energy efficiency improvements and costs of transmission line capacity expansion. $\mathbf{q}$ is the vector that contains capacity decisions (generation, energy efficiency, and transmission line capacity) for all periods in each region, and $\mathbf{y}$ is the vector of all production decisions. Constraint (3.3) is the market-clearing condition, where $\sum_j y_{jr}(s,t)$ is the total production of firms.[16] Constraint (3.4) ensures that imports and exports do not exceed transmission line capacity. Constraint (3.5) ensures that the emission reduction target is met.

[16] It is straightforward to show that price-responsive consumers increase consumption up to the level of electricity offered so that the market-clearing condition always binds.

3.3 Implementation in the numerical model

We quantify the long-run equilibrium of the European power market by using the model framework introduced in Section 3.2 and implementing short-term (demand shedding and shifting) and long-term demand response (endogenous investments in energy efficiency and exogenous technical progress in energy efficiency) in the combined dispatch and investment EU-REGEN model (see Chapter 1).[17][18]

The problem solved by the EU-REGEN model, which is finding a market equilibrium under the assumption of perfectly competitive markets and without demand response, is a cost-minimization problem and thus can be solved as a linear program. Adding short-term demand response to this model changes the structure of the underlying algebraic problem in regard to the new objective of maximizing welfare. The objective function can become quadratic or exhibit other kinds of nonlinearities. The most general way of solving such a problem is complementary programming. Karush-Kuhn-Tucker conditions are derived as the necessary first-order conditions for finding an optimum. The respective complementary variables are defined for each equilibrium condition (e.g., Takayama and Hashimoto, 1984). However, solving a detailed (i.e., large number of constraints) problem through complementary programming is not feasible given that a complementary variable has to be defined for each equilibrium constraint. Takayama and Uri (1983) emphasize that under certain conditions, a market equilibrium can be found by using quadratic programming, which requires (among other things) that the underlying problem be convex and the resulting market matrix positive semidefinite and, thus, symmetric (Jonghe et al., 2011). If these conditions are fulfilled, the market equilibrium can be found by solving the problem as an equivalent quadratic program by means of efficient algorithms that are tailored to solving convex problems (e.g., CPLEX). However, these conditions seriously constrain an extensive analysis of the impact of short-term demand response. Hence, in this chapter, the formulation of demand response in the numerical implementation must be adjusted with regard to those technical constraints.

[17] For parsimony, we introduced only the most important constraints in Section 3.2. More detailed information about the EU-REGEN model structure, the underlying data set, and additional constraints can be found in Chapter 1.

[18] Note that for the purpose of this chapter, time segments are weighted by mapping them to original hours based on minimizing the Euclidean distance, which allows us to still capture the temporal sequence of hours. This weighting algorithm differs from the one in Chapter 1, where time segments are weighted so as to minimize the sum of squared errors between the aggregated averages and the hourly averages for wind, solar, and demand profiles.

3.3.1 Short-term demand response

As a benchmark market outcome, we abstract from short-term demand response and investments in energy efficiency by taking a cost-minimizing approach and obtain reference values (denoted by subscript 0) for energy service demand, electricity demand, and electricity prices. The latter is derived from the dual variable of the market-clearing constraint. Energy service demand and electricity demand are exogenously given since there are no adjustments to energy efficiency in this benchmark. These reference values account for production decisions and investments in generation and transmission capacity. Under the specified emission target, we use these reference values as fixed points to specify demand shedding and demand shifting in our model.

Demand shedding leads to more (or less) consumption, whereas demand shifting is just the intertemporal reallocation of demand, that is, all shifts equalize over the respective period. Shedding accounts for the response to changing prices in a specific segment in comparison to a benchmark, that is, consumers decide to consume more (less) if the price is lower (higher). Shifting accounts for the response to changing prices in specific segments in comparison to prices in other segments, that is, consumers decide to shift some of their demand from segments with high prices to segments with low prices (and the other way around).[19] Note that shifting is temporarily limited and demand cannot be shifted for longer than a couple of time segments.

Demand Shedding As benchmark for demand shedding, we use the reference values determined from the benchmark market outcome described above. Remembering that $\epsilon_i^s < 0$ is the ability to shed, we obtain

$$x_{ir}\left(p_r\left(s,t\right)\right) \quad = \quad x_{ir,0}\left(s,t\right) + \epsilon_i^s \frac{x_{ir,0}\left(s,t\right)}{p_{r,0}\left(s,t\right)}\left(p_r\left(s,t\right) - p_{r,0}\left(s,t\right)\right). \tag{3.6}$$

Here, $x_{ir,0}\left(s,t\right)$ is the reference demand of a specific sector that serves as fixed point and the second term is shed demand. The difference between the actual and the reference price, $p_r\left(s,t\right) - p_{r,0}\left(s,t\right)$, is the willingness to shed. The fraction determines the overall level and ϵ_i^s constrains the total amount shed. Observe from Equation (3.6) that ϵ_i^s is defined as an own-price elasticity of demand. Thus, the magnitude of the increase is

[19] Regarding shedding, households might decide to switch on lights or the television when actual prices are low (or switch off when prices are high). Regarding shifting, households might decide not to use the dishwasher right now, but instead wait for a couple of time segments until the price is lower.

determined by an exogenously given price elasticity, which is obtained from empirical studies (e.g., Labandeira et al., 2017).[20]

Demand Shifting Figure 3.1 illustrates the effect of demand shifting between the specific segment s and another segment s'. Superscript sh denotes outcomes after the shifting process. Demand (gray curves show inverse demand, $p(x(\cdot))$) is the same in both segments, but supply (black curves show inverse supply, $p(y(\cdot))$) is lower in s than in s', which leads to higher prices in s. Consumers exploit the price difference $p(s) - p(s')$ and shift demand from s to s', yielding lower prices in s but higher ones in s' so that the price difference becomes smaller. This process is illustrated by the arrows and the parallel shifted demand curves (dotted gray curves show inverse demand after shifting, $p^{sh}(x(\cdot))$). There are two countervailing effects. First, demand is reduced in s (and increased in s') by Δx, which is the total amount of demand shifted. Second, demand is increased in s by $\Delta r(s)$ (and reduced in s' by $\Delta r(s')$) due to consumer response (demand shedding) to lower prices in s (and higher prices in s').

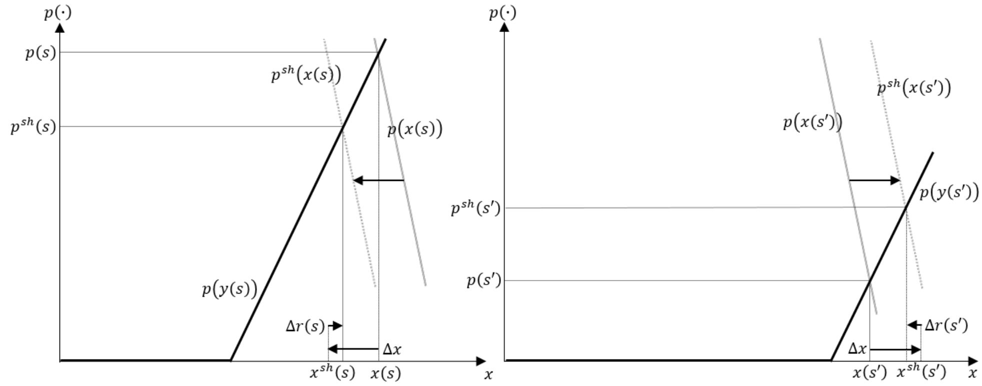


Figure 3.1: Demand shifting from periods with low supply to periods with high supply

In the numerical model, we determine the change in demand due to shifting by using the ability to shift ($\epsilon_i^{s,s'}$) and defining average reference demand of two segments s and s' by $\bar{x}_{ir,0}(s,s',t) := \frac{1}{2}(x_{ir,0}(s,t) + x_{ir,0}(s',t))$ and the average reference price by $\bar{p}_{r,0}(s,s',t) := \frac{1}{2}(p_{r,0}(s,t) + p_{r,0}(s',t))$. Using this, we obtain

$$\begin{aligned} x_{ir}(p_r(s,t)) &= x_{ir,0}(s,t) + \epsilon_i^s \frac{x_{ir,0}(s,t)}{p_{r,0}(s,t)}(p_r(s,t) - p_{r,0}(s,t)) \\ &\quad + \sum_{s' \neq s} \epsilon_i^{s,s'} \frac{\bar{x}_{ir,0}(s,s',t)}{\bar{p}_{r,0}(s,s',t)}(p_r(s,t) - p_r(s',t)), \end{aligned} \tag{3.7}$$

[20] For illustration, assume $\epsilon_i^s = -0.1$, $x_{ir,0}(s,t) = 50$ GW, $p_{r,0}(s,t) = 50$ €/MWh. If the current price is lower than the reference price, e.g., $p_r(s,t) = 40$ €/MWh, the consumer increases consumption by 1 GW. The relative price difference is -20% and thus the consumed quantity increases by 2%.

where $s' \neq s$ defines a subset of segments that does not contain segment s. The first line is identical to the specification of demand shedding in Equation (3.6) and the second line reflects demand shifting. $p_r(s,t) - p_r(s',t)$ is the price difference that determines the willingness to shift. The fraction ensures that shifts equalize over the entire period t, that is, the whole second line would vanish when summing up over all time segments. Finally, $\epsilon_i^{s,s'}$ constrains the total amount that can be shifted.[21]

Setting up the objective of welfare-maximization by using the specification of energy service demand in Equation (3.7) results in a complementary programming problem, which, as argued above, is numerically not tractable for the large number of constraints that are necessary to describe a multi-region electricity system. To be able to use a solution algorithm tailored to solving convex problems, we need to derive inverse (energy service) demand for each segment that depends only on the demand in this segment. Note that (from Equation (3.7)) energy service demand depends on the price in segment s but also on the prices in all segments with $\epsilon_i^{s,s'} \neq 0$. Given that we have one equation for each segment and the same number of unknown variables, this is, in principle, possible. However, the resulting objective function violates the necessary convexity (the market matrix is not positive semidefinite anymore) so that the problem is numerically not tractable. We avoid this problem by using an approximation of energy service demand. We use $p_{r,0}(s',t)$ instead of $p_r(s',t)$ because the best guess for prices in other segments is the reference price. Using $x_r(s,t) = \sum_i x_{ir}(s,t)$, $x_{r,0}(s,t) = \sum_i x_{ir,0}(s,t)$, and defining $\Gamma(s,t) := -\sum_i \epsilon_i^s \frac{x_{ir,0}(s,t)}{p_{r,0}(s,t)}$ and $\Gamma\left(s, s', t\right) := -\sum_i \epsilon_i^{s,s'} \frac{\bar{x}_{ir,0}(s,s',t)}{\bar{p}_{r,0}(s,s',t)}$ for clarity, we obtain the (approximated) inverse demand by

$$p_r(x_r(s,t)) = \frac{(x_{r,0}(s,t) - x_r(s,t)) + \Gamma(s,t)\, p_{r,0}(s,t) + \sum_{s' \neq s} \Gamma(s,s',t)\, p_{r,0}(s',t)}{\Gamma(s,t) + \sum_{s' \neq s} \Gamma(s,s',t)}, \tag{3.8}$$

which is a linear function of $x_r(s,t)$. Furthermore, we need to impose the constraint $\sum_s \sum_{s' \neq s} \Gamma(s,s',t)\,(p_r(s,t) - p_{r,0}(s',t)) = 0$ to ensure that demand shifts—even under the approximation—still equalize over all segments.

[21] For illustration, suppose that shifting is possible between segments 1 and 2. Prices are 100 €/MWh in segment 1 and 0 €/MWh in segment 2. Moreover, suppose that $\epsilon_i^{1,2} = -0.01$, $\bar{p}_{r,0}(1,2,t) =$ 50 €/MWh, $\bar{x}_{ir,0}(1,2,t) = 50$ GW. The total amount shifted from segment 1 to segment 2 is 1 GW, which accounts for 2% of the average reference demand between these two segments.

3.3.2 Energy efficiency

Consumers obtain utility from energy services but need to buy electricity. These can be treated as equivalent as long as there is a fixed transformation ratio from electricity into energy services. Energy efficiency improvements increase that ratio so that less electricity is required to consume the same amount of energy services.

This is illustrated by Figure 3.2. The demand for electricity, d, and energy services, x, are depicted on the x-axis; the price of electricity is shown on the y-axis. The black curve depicts inverse supply of electricity, $p(y)$, and the solid gray curve inverse energy service demand, $p(x)$, which are both time independent. Initially, demand for electricity (dashed gray curve, $p(d(0))$), is slightly lower than energy service demand. Improvements in energy efficiency does not change demand for energy services but electricity demand is reduced by ΔQ^{ee} (see the arrow and the dotted gray curve, $p(d(t))$). This reduces the equilibrium price and consumers reduce the effect of energy efficiency improvements by consuming more energy services and, thus, more electricity. We call $\Delta r^{ee} = \Delta Q^{ee} - (d(0) - d(t)) = x(t) - x(0)$ the *rebound* of energy efficiency improvements and $\Delta r^{ee}/\Delta Q^{ee}$ is the corresponding *rebound effect*. By including the rebound effect, the price finally drops from $p(0)$ to $p(t)$.[22] Finally, observe that energy efficiency improvements increase welfare due to lower production costs (gray area on the left) and due to the rebound, that is, increased energy service consumption (gray area on the right).

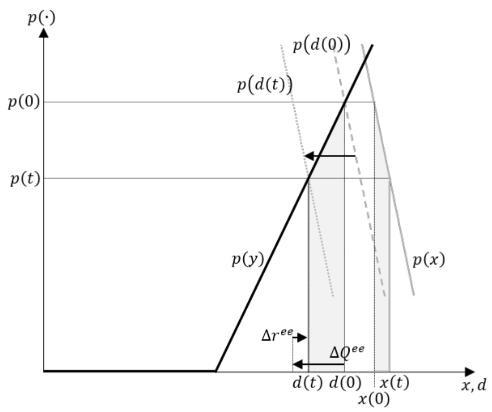


Figure 3.2: Rebound effect of energy efficiency improvements

We assume that energy efficiency is measured in absolute terms. First of all, this formulation accounts for the sparse availability of energy efficiency investment costs, which are only available per unit of energy efficiency (see Section 3.4). Moreover, an additive term

[22] The magnitude of this rebound critically depends on the shape of (inverse) demand and supply. However, in a partial equilibrium setting, the rebound never overcompensates the initial savings and thus never leads to "backfire" (see Lemoine, 2016).

allows to avoid a non-linear constraint and to keep the model tractable. However, under the assumption of constant costs for energy efficiency, this formulation would result in one unit of energy efficiency relative to the level of electricity demand becoming cheaper over time. We counteract this effect by assuming an increasing marginal cost curve for energy efficiency, which is also proposed in the literature (see Section 3.4).

We specify sector-specific electricity demand by

$$d_{ir}(s,t) \quad = \quad x_{ir}(s,t) - \gamma(t)\, Q^{ee}_{ir}(t)\,. \tag{3.9}$$

$Q^{ee}_{ir}(t)$ is the aggregated capacity of energy efficiency improvements that obtains endogenously from investments. $\gamma(t)$ is the performance factor of the respective energy efficiency measure. The development of $\gamma(t)$ over time reflects exogenous technological progress in energy efficiency. We take this approach so as to account for the fact that exogenous progress depends on endogenous investments in energy efficiency.

3.4 Calibration of the numerical model

In the following we describe the quantification of parameters relevant for depicting demand response in the EU-REGEN model.[23] We differentiate the demand side into the industry, residential, commercial, and transport sectors. Regarding the abilities to shed (ϵ_i^s) and shift demand ($\epsilon_i^{s,s'}$), we use existing estimates that vary widely depending on the specific sector, country, sample period, and estimation method (e.g., Labandeira et al., 2017; Jamil and Ahmad, 2011; Huntington et al., 2017). The overview in Huntington et al. (2017) indicates that the residential sector generally has better ability to shed demand than industry, transport, or commercial sectors. This analysis uses estimates from the meta-analysis conducted by Labandeira et al. (2017). As a default assumption, we set the ability to shed demand to the values shown in Table 3.1. Moreover, as indicated in Huntington et al. (2017) and Taylor et al. (2005), the ability to shift (called cross-price elasticity in those works) seems to be moderate in comparison to the ability to shed. Thus, we assume that the abilities to shift occurs in the four previous and subsequent time segments and is 10% of the ability to shed (see Table 3.1).[24]

[23] See Chapter 1 for the general calibration of the EU-REGEN model and the underlying data set for the supply side. Remember that the base year is 2015 and the time horizon is 2050. Dispatch and investment decisions are optimized in five-year steps, whereas 121 intra-annual segments are used for computational reasons.

[24] This assumption ensures that the symmetry and positive semi-definite requirements (see Section 3.3) are satisfied.

Table 3.1: Abilities to shed and shift demand

	Ind	Res	Com	Tra
$\epsilon^{s,s}$	−0.15	−0.2	−0.1	−0.1
$\epsilon^{s,ss}$	−0.015	−0.02	−0.01	−0.01

To approximate the existing level of energy efficiency, we assume that each region's current level is represented by a relative measure (denoted by ζ_r) reported in the *Odyssee Database* (see Enerdata, 2018). We assume that demand for electricity and energy services is the same in 1990 and all differences after 1990 reflect energy efficiency improvements. We obtain the initial level of energy efficiency from $EE_r\,(2015) = \zeta_r\,\overline{d}_r\,(1990)$, where $\overline{d}_r\,(1990)$ is the annual electricity demand in 1990. Table C.1 in Appendix C.1 shows the resulting 2015 energy efficiency capacities and the values for ζ_r and $\overline{d}_r\,(1990)$.

We assume that the performance factor increases by 5% with every new vintage. For parsimony, we assume a default performance of $\gamma\,(2015) = 1$. Moreover, the depreciation rate for energy efficiency investments δ^{ee} is set to 10% for all sectors and regions. Both assumptions, will be varied in Section 3.5 to test the sensitivity of our results to these assumptions.

For demand growth projections by country, we use numbers from the *e-HIGHWAY 2050 Project* (see Bruninx et al. (2015) and Chapter 1), which expects an EU-wide demand growth of 34% in the period 2015–2050. We apply the country-specific growth rates to energy service demand and obtain the resulting electricity demand from endogenous energy efficiency improvements (Table C.1 in Appendix C.1). Moreover, we take each sectors' share in the 2015 electricity demand from Enerdata (2018) and assume these shares to remain constant over time.

Data availability is less than optimal when it comes to the costs of energy efficiency investment. We use Germany as the reference and approximate the costs function by a stepwise function that is characterized by five classes with each of them being characterized by different investment costs. Each class has an upper size limit, which represents the limited potential for energy efficiency in a class. We base our assumptions on the costs proposed by Steurer (2016) and Huntington (2011a,b). For the industrial sector, we use the energy efficiency supply curve for the German industrial sector from Steurer (2016). Huntington (2011a,b) shows that the opportunity costs of energy efficiency are lower in the residential sector than in the industry sector. Hence, we scale costs for industry energy efficiency investments by 0.5 to approximate the costs for the residential sector. Furthermore, we adjust class sizes in proportion to the 2015 German residential electricity demand relative to the electricity demand of the German industrial sector. We use the same approach (scaling by a factor of 0.5 and proportional class sizes) for transport and commercial. Table 3.2 shows class sizes as well as costs for Germany.[25] We assume the same costs for all other regions and determine the size of each class by using the sector-specific demand of the other regions relative to the sector-specific demand in Germany.

Table 3.2: Energy efficiency supply classes for Germany

Class	Ind		Res	Com	Tra	Res, Com, Tra
	Size [GW]	Costs [€/kW]	Size [GW]			Costs [€/kW]
1	2	2,500	1,23	1,40	0,11	1,250
2	3	6,000	1,85	2,10	0,16	3,000
3	1	10,000	0,62	0,70	0,05	5,000
4	1	17,000	0,62	0,70	0,05	8,500
5	1	30,000	0,62	0,70	0,05	15,000

With respect to the existing level of energy efficiency, it is distributed over classes in ascending order, meaning that all the existing level belongs to class 1. If the existing level exceeds the size of a class, the remaining is assigned to the next class. This allows determining the remaining energy efficiency potential and its costs for each sector in a region.[26] Moreover, we assume that the existing level of energy efficiency does not depreciate.

3.5 Results

We begin our presentation of results by characterizing the long-run equilibrium of the European power market under different assumptions of demand response. Next, we quantify the role that energy efficiency plays in reaching the goals of climate policy. We end by discussing how the optimal level of energy efficiency (EE) changes under varying assumptions. For parsimony, we use the term *energy efficiency investments* to refer to accumulated additions.

3.5.1 Long-run market equilibrium under responsive demand

Energy efficiency Under responsive demand (i.e., with the default assumptions outlined in Section 3.4), the optimal (EU-wide) investments in energy efficiency gradually increase until 2030, peaks in 2040, and then depreciates to 42 GW in 2050 (see Table 3.3), resulting in an annual electricity demand reduction of 394 TWh (11%) in 2030 and 429

[25] Note that the cost assumptions in this table directly feed in the costs from energy efficiency $C_{ir}^{ee}(\cdot)$ in Section 3.2.

[26] Note that the already existing level of energy efficiency reduces the remaining energy efficiency potential.

TWh (10%) in 2050.[27] In relation to the 2015 level of energy efficiency, the 2030 level represents a further 69% increase in energy efficiency.[28] Interestingly, there is a massive build-up in the first investment period (2020), indicating that the current, EU-wide level of energy efficiency is below its socially optimal level.

Table 3.3: Initial level of energy efficiency (2015) and investments [GW]

Region	2015	2020	2025	2030	2035	2040	2045	2050
Europe	60.4	32.3	38.7	41.8	44.1	44.2	44.0	42.3
Britain	10.5	0.0	0.5	0.5	0.5	0.5	0.4	0.4
Eastern Europe-SE	3.6	3.0	4.1	4.1	5.2	5.2	5.2	5.0

Regarding future investments, we observe a heterogeneous spatial distribution. Up to the (EU-wide) level peak in 2040, the northeast region (Eastern Europe-NE) shows with 5.8 GW (583%) the highest increase of its energy efficiency level, followed by the southeast region (Eastern Europe-SE, 5.2 GW, 143%), the southwest region (Eastern Europe-SW, 5.5 GW, 281%), and Italy with 4.7 GW (124%). For Scandinavia, Britain, and North Germany, it is optimal to make only minor or no investment. Table 3.3 shows the detailed development for Britain (United Kingdom and Ireland) and Eastern Europe-SE (Bulgaria, Greece, and Romania). The case of Britain can be explained, to a certain extent, by the already high level of energy efficiency and a high quality of wind resources.[29] Our results indicate that it is optimal to improve energy efficiency mainly in regions that are either on the border of the European power market or do not have access to high-quality wind (e.g., Eastern Europe-SE).[30] In Eastern Europe-SE, we observe a catch-up effect in 2020. The attractiveness of investments in energy efficiency after 2020 is driven by low-quality wind resources and the absence of links to other regions due to its position on the spatial fringe. Note that solar irradiation in Eastern Europe-SE is high, but does not influence energy efficiency investment. In general, the diurnal solar irradiation pattern is not a substitute for the constant demand reduction from energy efficiency, whereas the seasonal wind pattern is a substitute.

With respect to sectoral distribution, the industrial sector (28 GW) and the residential sector (20 GW) have much higher initial levels of energy efficiency than the commercial

[27] Note that the reduction in electricity demand in 2050 is larger than that in 2030, even though energy efficiency capacity slightly decreases, due to the exogenous technological progress in energy efficiency described in Section 3.4.

[28] See Table C.1 in Appendix C.1 for regional- and sector-specific figures for the initial level of energy efficiency, and Table C.2 in Appendix C.2 for the regional-specific development over time.

[29] The United Kingdom has the highest initial level of energy efficiency, followed by Germany (9.5 GW) and France (6.2 GW). See Table C.2 in Appendix C.2 for more details.

[30] In particular, when looking at Scandinavia and North Germany, it becomes obvious that access to high-quality wind resources prevents investments in energy efficiency.

(11 GW) and transport (1 GW) sectors.[31] However, the equilibrium energy efficiency level by demand sector shows that it is chiefly the residential, commercial, and transport sectors that engage in investments. The transport and commercial sectors have a low existing level of energy efficiency and thus can still make energy efficiency improvements at relatively low cost. The residential sector increases its energy efficiency more than the industrial sector due to lower investment costs (see Table 3.2).

Residual peak load Short-term demand response reduces residual peak load (i.e., the time segments with the highest electricity demand net of intermittent renewables such as wind and solar) by 8% in 2015 and by almost 33% in 2050.[32] We decompose this reduction by comparing the outcome with one where there is no investment in energy efficiency. The contribution of energy efficiency is one-third of the total reduction and the share of shedding and shifting accumulates to two-thirds. For the residual off-peak load (i.e., the time segments with the lowest residual load), short-term demand response contributes to an increase of the residual off-peak load by almost the same amount as the residual peak load decreases.

Capacity and generation path We now turn to the long-run equilibrium of generation and capacities. Responsive demand particularly impacts substitution among technologies on the supply side. The impact of demand response can be found by comparing market outcomes under a *full demand response* scenario (i.e., with short-term demand response and energy efficiency) to those under a *no demand response* scenario, which is illustrated in Figure 3.3. The figure shows the development of annual generation for relevant technologies under full demand response (left) and no demand response (right). Under full demand response, wind power is the major technology, with an annual generation-share of 24% in 2030 and 40% in 2050. Wind power is accompanied by an increasing contribution of gas power (6% in 2030, 19% in 2050), and solar PV (3%, 11%). In 2050, under no demand response, the accumulated share of wind and solar PV decreases from 51% to 35%, whereas the share of gas increases from 19% to 25%. Demand response is a substitute for flexible generators such as gas turbines. When consumers are able to react to changing prices, less gas capacity is needed to balance intermittent generation from renewables. Moreover, the balancing does not come at a higher cost so that the relative competitiveness of wind and solar PV increases. Furthermore, coal-powered technologies stay active longer under responsive demand because substituting gas power is less competitive in the presence of responsive demand.

---

[31] See Section 3.4 and Table C.1 in Appendix C.1.

[32] Note that no capacity investments take place in 2015, but capacities can be decommissioned and responsive demand influences (residual) peak and off-peak load.

Interestingly, in neither scenario is there investments in CCS on the basis of coal and gas. However, bio power in combination with CCS (BECCS) does not enter the European power market under responsive demand, whereas under no demand response little BECCS will be built at the end of the time horizon.[33]

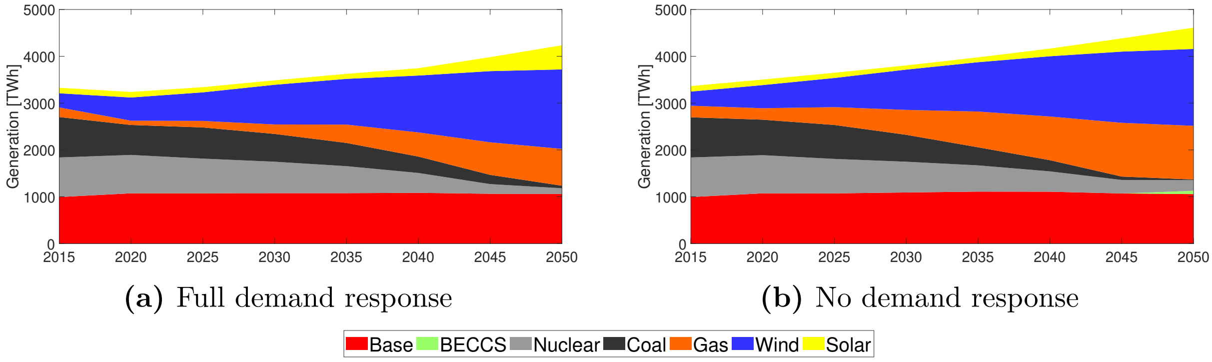


Figure 3.3: Long-run generation path with and without demand response

The effect of responsive demand is also visible on the capacity investment path. Again, comparing the outcomes of a full demand response scenario and no demand response scenario (see Figure 3.4) shows that responsive demand not only promotes higher generation (e.g., due to avoided curtailment) but also the build-up of wind and solar PV in the long run. The 2050 wind power capacity rises by 5% with responsive demand and the stock of solar PV capacity experiences an increase of 23%. In analogy to the generation path, the further capacity build-up of both technologies is compensated for by reduced stocks of mainly gas power as well as nuclear and BECCS.

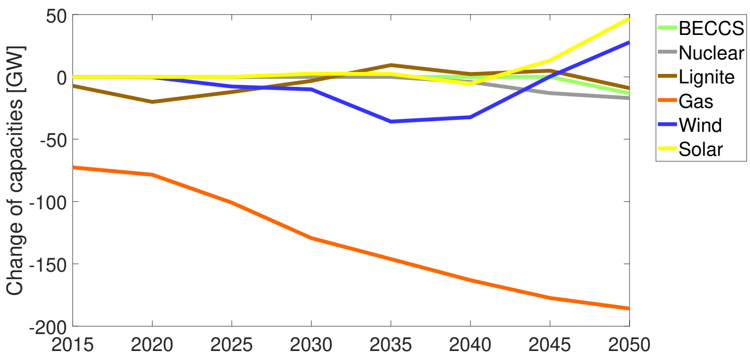


Figure 3.4: Change of generation capacity path with full demand response (compared to no demand response)

It is important to emphasize that responsive demand leads to higher utilization rates of generation capacity. For example, wind power capacity is lower under full demand

[33] See the Subsection 3.5.2 on decarbonization.

response up to 2040, although its generation is higher. Moreover, the 2050 capacity stock across all technologies is 9% lower with responsive demand. Observe that under responsive demand, more than 70 GW of gas capacity is decommissioned immediately in 2015. Gas capacity decreases further as the share of wind and solar PV generation in the system increases (compare Figures 3.3 and 3.4). This effect mainly comes from short-term demand response. The effect of energy efficiency investments on this development is small (33.5 GW in 2030 and 31 GW in 2050).

Electricity prices and welfare The switch to more capital-intensive renewable energy technologies and energy efficiency further impacts expenditures on the supply side, and the equilibrium electricity prices. Whereas until 2050, capital expenditures experience only a minor decrease with responsive demand, the sum of incurred variable costs decreases by 22%.

To decompose the effects of short-term demand response and energy efficiency improvements on price levels, we compare the (quantity) weighted average electricity prices over all regions under four scenarios: *no demand response*, *EE investments only*, *short-term response only*, and *full demand response* (see Table 3.4). Intuitively, the price is highest under no demand response; we thus chose this scenario as the reference and set the level to 1. Observe that the average electricity price is decreasing with demand response. Energy efficiency improvements play a dominant role for prices in 2020 and 2025. The build-up of energy efficiency capacity (see Table 3.3) leads to a price drop of 13% in 2020, which is phased out over time. From 2030 on, the impact of short-term demand response is dominant. In 2050, short-term demand response accounts for almost two-thirds of the price decrease, whereas energy efficiency delivers only one-third, which is in line with the impact shares of short- and long-term demand response on residual peak load.

Table 3.4: Change of (EU-weighted average) electricity prices under different levels of demand response (compared to no demand response)

Scenario	2015	2020	2025	2030	2035	2040	2045	2050
EE investments only	1.00	0.87	0.93	0.93	0.95	0.98	0.97	0.99
Short-term response only	0.99	0.98	0.96	0.95	0.95	0.96	0.95	0.95
Full demand response	0.98	0.87	0.89	0.90	0.92	0.92	0.92	0.92
in Britain	1.00	0.95	0.91	0.90	0.95	0.90	0.91	0.89
in Eastern Europe-SE	1.00	0.65	0.67	0.70	0.78	0.85	0.91	0.91

All regions experience a long-run price decrease, which is in line with Gambardella et al. (2016). The northern regions experience the strongest impact due to their common characteristic of high-quality wind resources.[34] In the case of Britain, responsive demand

[34] See Table C.3 in Appendix C.2 for a regional differentiation of prices under full demand response.

can reduce the 2030 equilibrium price by 5% and for 2050 by another 6%. The lowest decrease is in the southwestern region (4% in 2050). For Eastern Europe-SE, prices drop due to the build-up of energy efficiency (see Table 3.3). However, in the long-run (relative) prices are increasing again and, finally, are higher than those in Britain because the higher wind potential in Britain leads to more intra-annual price differences so that the effect of short-term demand response is higher.

We identify the welfare implications of energy efficiency by again decomposing the effect of short-term demand response and energy efficiency. Results show that the availability of short-term demand response (short-term response only scenario) can maintain 90% the overall discounted European welfare (for the time period 2015–2050) in the power market under the full demand response scenario. Only 10% of overall European welfare hinge on the optimal adjustment of energy efficiency. However, it is important to emphasize that we cannot evaluate the actual welfare effect of short-term demand response. Short-term demand response comes at no costs (in contrast to energy efficiency) in our framework, its level is exogenously set, and hence we do not determine its welfare-maximizing level.

Rebound effect As described in Subsection 3.3.2, energy efficiency investment leads to a *rebound effect* due to reduced prices.[35] Lower prices do not occur only due to energy efficiency improvements but also due to the dynamic adjustment of capacities. To distill the rebound effect from energy efficiency investments, we need to determine the change in electricity demand due to the dynamic adjustment of capacities and short-term demand response. To do so, we first determine electricity demand under the *short-term response only* scenario that fully abstracts from energy efficiency investments.[36] The rebound for this scenario is determined by calculating the expected savings, and subtracting the observed decrease in electricity demand over time (61 TWh for 2030, see Table 3.5). Second, we compare this result with the rebound under the *full demand response* scenario (103 TWh for 2030). The rebound due to energy efficiency investments is given by the difference between these two scenarios (42 TWh). To calculate the final rebound effect, we just need to divide the rebound by expected savings (see Figure 3.2). Table 3.5 shows a rebound effect from energy efficiency investments of 9% in 2030 as well as in 2050.

In the following, we focus on the rebound effect from energy efficiency investments. Observe that the rebound effect remains constant over the covered time horizon. The magnitude of this effect is rather small compared to the empirical results of other studies (e.g., Wang et al., 2016; Chakravarty et al., 2013; Wei and Liu, 2017). The reason for

[35] Note from Section 3.1 that we cover the direct (or partial equilibrium) rebound effect only and abstract from the indirect (or general equilibrium) one.

[36] Note that, under this scenario, there is still the initial level of energy efficiency.

Table 3.5: Decomposition of rebound effect

Scenario	Category	2030	2050
Short-term only	Full rebound from lower prices [TWh]	61	99
	Full rebound from lower prices [TWh]	103	137
Full demand response	Rebound from EE investments [TWh]	42	38
	Rebound effect from EE investments [%]	9	9

the difference is threefold. First, our analysis does not capture the general equilibrium rebound effect (see Section 3.1). However, Böhringer et al. (2018) suggest that the general equilibrium part of the rebound is rather small (16.5% for electricity in the EU) in comparison to the partial one (57%). Second, empirical studies rely on engineering projections, which might overestimate the true savings due to, for example, consumer heterogeneity (see Fowlie et al., 2018; Allcott and Greenstone, 2017). Third, the size of the rebound effect is driven by the sensitivity of short-term demand response. For example, higher price elasticities of demand lead to greater quantity adjustments. In Table 3.6, we verify this for 2050 by using doubled to fivefold abilities to shed and shift (see Table 3.1 for the default values).[37] Doubling the abilities leads to a more than doubled rebound effect, whereas the fivefold abilities result in a rebound effect of 29%. The qualitative result—that the rebound effect is larger when gradually increasing the abilities—is not surprising. More interestingly, even with fivefold abilities to shed and shift, we cannot confirm that the rebound effect is of much relevance for the long-run equilibrium of the European power market.

Table 3.6: Sensitivity of rebound effect in 2050

Ability levels $\epsilon^s, \epsilon^{s,s'}$	1×	2×	3×	4×	5×
Rebound from EE investments [TWh]	37	81	104	115	125
Rebound effect from EE investments [%]	9	19	24	27	29

3.5.2 The role of energy efficiency for decarbonization

Abatement channels In Section 3.5.1, we show that energy efficiency investments reduce annual electricity demand by 10% in 2050. Now, we want to shed further light on energy efficiency by analyzing its role for decarbonization. We quantify the contribution of different abatement channels—intermittent renewables such as wind and solar, energy efficiency, fuel switching, and nuclear power—to decarbonization of the European power market. We do so by comparing the market outcomes under a *climate policy* (80% emission reduction target in our default version) and under the *absence of a climate policy*

[37] For example, doubling the ability of the industrial sector would lead to $\epsilon^{s,s} = -0.3$ and $\epsilon^{s,ss} = -0.03$.

(no reduction target).[38] Figure 3.5 shows the shares of different abatement channels. The uppermost line represents emissions under the absence of a climate policy. Emissions increase from 1,040 $MtCO_2$ in 2015 (by 15%) to 1,200 $MtCO_2$ in 2050. The lowest line shows emissions under an 80% reduction target, so that emissions reach a level of 290 $MtCO_2$ in 2050. The area in between the uppermost and lowest line represents emission reductions due to a climate policy. We find that the majority of emission reductions comes from intermittent renewables (53% in 2050) and fuel switching (36%). Observe that emissions drop in 2020 due to investments in energy efficiency, even without a climate policy (see initial drop of emissions in Figure 3.5). Energy efficiency investments increase even further until they peak in 2040 (see Table 3.3). However, in analogy to the results in Section 3.5.1, energy efficiency plays a minor role for meeting the reduction target in the long run (11% in 2050). The reason is that energy efficiency investments are beneficial even without a climate policy. Hence, in presence of a climate policy, energy efficiency helps with the total burden of reduction and alleviates the emission target (observe that until 2030 there is almost no difference between the policy and the no policy scenario). This allows a technology-mix with higher emission intensity so that coal power stays longer active (see Figure 3.3).[39]

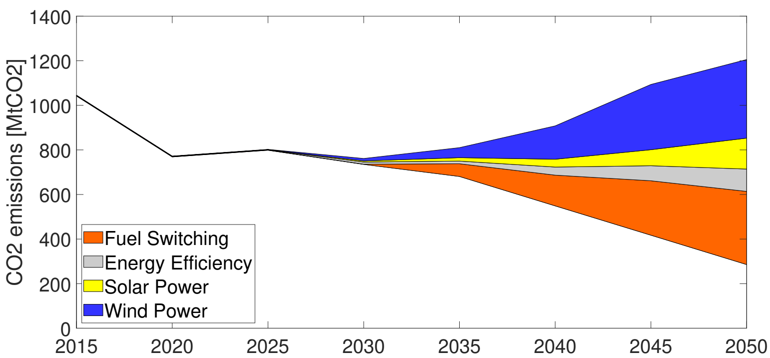


Figure 3.5: Contribution of different abatement channels to climate policy

To distill the effect of short-term demand response on a climate target, we conduct the same exercise as in the previous paragraph while omitting short-term demand response. The contribution of intermittent renewables to emission reductions falls to 49% (compared to 53% with short-term demand response). This is compensated for by an increased role for fuel switching (49%). Thus, when defining the contribution of short-term demand response to decarbonization (under a reduction target) as the increased role of renewable

[38] The absence of a climate policy does not necessarily mean that there will be no investment in energy efficiency, renewables, or gas power as well as no utilizing of short-term demand response.

[39] The mechanism is similar to the finding of Böhringer and Rosendahl (2010) that an emission reduction target in combination with a quota for renewables promotes the dirtiest technology, meaning that coal stays and gas leaves the market. In our model, we do not have a green quota but, rather, a central planner investing in energy efficiency.

energies, it contributes to 4% of emission reductions. The mechanism behind is discussed in Subsection 3.5.1: the non-existence of a cheap flexibility option (short-term demand response) reduces the relative competitiveness of intermittent renewables in comparison to gas power. Without short-term demand response, energy efficiency plays an even smaller role (2%), either due to energy efficiency investments that are beneficial even without a climate target or due to substituting effects with gas power.

Marginal abatement costs The impact of a climate policy in economic terms is captured by the marginal abatement costs, which is the dual variable of the carbon-emission constraint in our model. As shown in Table 3.7, the marginal abatement costs increase over time with a tight climate target. This holds for *no demand response* as well as for scenarios with demand response. Responsive demand has its merits in reducing the costs of the technology that abates on the margin. The marginal abatement costs are significantly lower with *full demand response* (51 compared to 73 €/tCO_2 for no demand response). However, energy efficiency and short-term demand response are equally important for lowering the marginal abatement costs. We calculate this by using scenarios that either abstract from short-term demand response (*EE investments only*) or from investments in energy efficiency (*short-term response only*). The results are shown in Table 3.7. Interestingly, the interaction of both mechanisms holds potential for reducing the marginal abatement costs. Gas power serves as base load generator as well as a flexible generator to balance the supply of renewables such as wind and solar. Now, energy efficiency reduces the need for base load gas power in the *EE investments only* case but, still, gas power is needed due to its flexibility. In contrast, with *short-term response only*, gas power is less needed as a flexibility option, but is still required as base load generator. Thus, gas power is still crucial for the marginal abatement technology. This prevents stronger price drops with regard to energy efficiency investments or short-term demand response. However, combining both demand side measures has a subadditive effect because the need for gas power drops tremendously.

Table 3.7: Marginal abatement costs [€/tCO2]

Scenario and climate target	2015	2020	2025	2030	2035	2040	2045	2050
No demand response (80%)	0	0	0	8	14	26	46	73
EE investments only (80%)	0	0	0	2	4	18	34	65
Short-term response only (80%)	0	0	0	3	8	19	36	64
Full demand response (80%)	0	0	0	1	1	12	27	51
No demand response (95%)	0	2	10	17	25	44	76	91
Full demand response (95%)	0	0	0	3	13	25	58	82

When looking at a tighter climate target (i.e., a 95% reduction target), the ability of responsive demand to reduce the marginal abatement costs diminishes. While demand response reduced the carbon price in 2050 by 29% under an 80% reduction target, demand response accounts for a reduction of only 10% under a 95% target (see Table 3.7). Moreover, the marginal abatement costs increase significantly, for three reasons. First, the tighter climate policy is pushing almost all coal and a significant share of gas generation (and capacity) out of the market. More expensive abatement technologies (BECCS, nuclear) must be used. Second, the tighter climate target has a feedback effect on the ability to reduce carbon emissions with intermittent renewables. The ability to shed and shift demand stays constant but less gas capacity reduces the system flexibility and thus the ability to balance the intermittent supply of wind and solar so that the subadditive effect from the less stringent climate target above vanishes. Third, more expensive energy efficiency measures will be used to allow for increased carbon intensity of the remaining generation-mix.

3.5.3 Robustness of investments in energy efficiency

We now relax assumptions made in Section 3.4 about depreciation rate, initial performance factor, and exogenous technological progress of energy efficiency in order to look into the sensitivity of energy efficiency investments. We identified energy efficiency as one way of reducing carbon emissions, but its final impact on demand (10% reduction) and emission reduction (11%) is small compared to that of intermittent renewables and fuel switching. The assumptions about costs and performance of the latter two are based on a broad literature (e.g., Schröder et al., 2013), whereas the assumptions of short-term demand response and energy efficiency are less well established.[40] For example, the energy efficiency supply curve is grounded on Steurer (2016) (for the industrial sector), whereas reduced costs for other sectors rely on Huntington (2011a,b). Moreover, there is an ongoing debate about the size of the energy efficiency gap (Gillingham and Palmer, 2014) and the reasons for it (Fowlie et al., 2018; Allcott and Greenstone, 2017).[41]

Depreciation rate sensitivity Note that the carbon constraint is tightening, especially, from 2030 to 2050 (see Figure 3.5). However, we see that this has no influence on energy efficiency investments with almost no new investments in energy efficiency between 2030 and 2050 (see Table 3.3). We test the robustness of this result by varying the depreciation rate (δ^{ee}). Table 3.8 shows the results. Note that the electricity demand reduction refers to a situation without any (additional) energy efficiency investments. Increasing or decreasing the default depreciation rate of 10% leads to minor adjustments

[40] Note that assumptions about short-term demand response have already been tested in Table 3.6.

[41] We refrain from showing sensitivity on energy efficiency potentials and costs because the effect of varying the performance factor is analogous. For example, doubling the performance factor has the same effect as doubling the energy efficiency potential by class while assuming half costs.

in investment but does not change the overall picture. Energy efficiency constantly leads to a reduction in electricity demand of around 10%. Also the lack of a build-up between 2030 and 2050 remains.

Table 3.8: Sensitivity regarding depreciation rate

Depreciation rate δ^{ee} [%]	0	1	5	10	15
EE investments until 2030 [GW]	44.05	43.97	42.47	41.78	39.56
Electricity demand reduction [%]	11.59	11.58	11.22	11.17	10.64

Performance parameter sensitivity In Section 3.1, we discuss the energy efficiency gap and provide an overview of arguments on this topic. One explanation for the energy efficiency gap are exaggerated engineering projections. Within the framework of this chapter, this can be captured through a sensitivity analysis on the delivered impact of energy efficiency, that is, the performance factor ($\gamma(t)$; see Equation (3.9)). Values smaller than 1 represent a reduced performance, for which there is empirical evidence (e.g., Allcott and Greenstone, 2017; Fowlie et al., 2018). Varying this parameter shows the effect of the delivered impact of energy efficiency on its equilibrium level (see Table 3.9). For low performance values, there is no investment in energy efficiency.[42] For $\gamma > 0.15$, the central planer starts investing in energy efficiency; however, the results show that a level of $\gamma \geq 0.35$ is required to achieve any significant investment in energy efficiency. Assuming a better energy efficiency performance and hence going beyond the default value of 1, leads to a minor increase in the optimal energy efficiency level. As a consequence, the actual electricity demand reduction is minor for small values of γ and increases to 19% when reaching an energy efficiency performance of $\gamma = 1.5$. Observe that the robustness of the economic viability of energy efficiency investments is strongly dependent on their delivered impact. The results identify a threshold of 0.35 before there will be any significant investment in energy efficiency, which is close to the calculated value of true savings in Fowlie et al. (2018).

Table 3.9: Sensitivity regarding performance parameter

Initial performance parameter γ	0.2	0.5	0.7	1.0	1.2	1.5
EE investments until 2030 [GW]	4.71	29.14	33.57	41.8	42.66	47.58
Electricity demand reduction [%]	0	4	6	11	14	19

Technological progress sensitivity As a default assumption, the performance parameter increases by 5% every five years. The impact of this exogenous technological

[42] Note that the variation discussed in this paragraph refers to the value of γ in 2015. We still assume the 5% increase of γ over time due to exogenous technological progress.

progress is tested by varying the initial performance (γ in 2015) between 0 and 1.5, and omitting the increase of γ over time or using even higher rates (10% and 15%). The resulting equilibrium levels of energy efficiency for 2030 are shown in Figure 3.6. Observe that the level of energy efficiency investments depends very little on the assumed exogenous technological progress. However, higher progress rates tend to increase energy efficiency investment. In particular, for values around the threshold of 0.35, that was identified in the previous paragraph, the assumed progress has an influence, but for our default assumption of $\gamma = 1$ there is almost no difference.

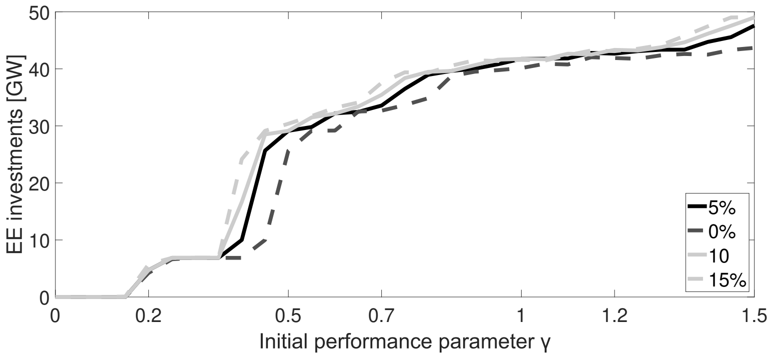


Figure 3.6: Energy efficiency investments for varying performance and technological progress in 2030

3.6 Discussion and conclusion

In this chapter, we developed a framework for implementing short-term demand response and energy efficiency in a multi-region partial equilibrium power market model. We use this framework to determine the optimal level of energy efficiency investment and its implications for the transition of the European power market under a climate target.

Some of the extant literature emphasizes that the interaction between short-term demand response and energy efficiency might lead to much lower energy demand reductions due to the rebound effect. We calculate a rebound effect from energy efficiency investment of 9% in 2050, so that electricity demand is finally reduced by only 10%. This outcome is robust with respect to the depreciation rate, performance, and the assumed rate of exogenous technological progress in energy efficiency. Higher rebounds are calculated for more sensitive short-term demand response. Having in mind that the empirical literature indicates that the short-term sensitivity of electricity demand is rather low (e.g., Labandeira et al., 2017), rebounds higher than 30% are extremely unlikely and the future role of the rebound effect, at least in the power sector, seems to be *overplayed*.[43]

[43] Gillingham et al. (2013) use this wording for the estimated rebound effect in the US car sector.

We show that the merits of demand response in supply side adjustment also need to be considered. Short-term demand response and energy efficiency enhance the role of wind and solar power, and change the composition of the stock of dispatchable technologies. Energy efficiency reduces demand and thus the need for base load generators so that nuclear capacity diminishes. Short-term demand response offers flexibility in integrating intermittent renewables and hence diminishes the role of gas power; bio power with CCS vanishes completely. Coal power stays active even longer because energy efficiency alleviates the emission reduction constraint for the supply side, which allows for a higher emission intensity across the remaining technologies and hence increases the relative competitiveness of coal power.

Investments in energy efficiency contribute 11% toward meeting the 80% emission reduction target of 2050 (compared to 1990). Here, renewables (53%) and fuel switching (36%) play dominant roles. Energy efficiency investments and short-term demand response reduce the carbon price almost equally (reduction of 8 or 9 €/tCO_2, respectively). We find subadditive effects when the measures are combined (reduction of 22 €/tCO_2), so that the final carbon price is at 51 €/tCO_2 in 2050. Energy efficiency reduces generation of gas power, which still remains crucial to the marginal abatement technology because it offers the necessary flexibility to integrate intermittent renewables. As soon as short-term demand response is also adding to the ability to deal with intermittency, instead of gas power playing this role, the carbon price drop is reinforced.

To conclude, the market value[44] of energy efficiency drops with high shares of intermittent renewables. If wind turbines and solar PV generate plenty, prices in the power market are close to or even zero and a reduction of electricity demand has no additional value to the market. Thus, energy efficiency (and also the connected rebound effect) plays a minor role for the long-run equilibrium of the European power market, but it is rather a technology required for the mid-run between 2020 and 2030. Instead of relying on energy efficiency, the focus of policy makers should rather turn towards short-term demand response, which plays a crucial role for the future technology-mix. A first step would be to incentivize short-term demand response by promoting the installation of smart meters in household, subsidizing the development of smart devices that communicate with smart meters and can be controlled remotely, and, even more important, requiring electric utilities to offer flexible tariffs; otherwise consumers do not benefit from the temporal reallocation of electricity demand.

The impact of the short-term demand response, which is cautiously estimated in this chapter, is not small. More than 70 GW of gas power capacity would be decommis-

[44] See Lamont (2008) for the definition of the market value of a generation technology.

sioned immediately. Between 2020 and 2030 almost no additional gas capacity is needed, whereas not considering the possibility of demand shifting and shedding leads to a massive build-up of gas capacity already in the mid-run. Moreover, an electricity system with centrally located gas capacity has substantially different implications with regard to network topology than a system with decentralized consumers offering flexibility by means of short-term demand response. This emphasizes the importance of prompt action by policy makers to avoid path dependencies, which would lead to a suboptimal implementation of the transformation path of the European power market and delays in the required infrastructure adjustment. In particular, policies suitable to promote the installation of gas power, such as capacity mechanisms, seem to work against the notion of reaching a socially optimal technology-mix for this path.

This chapter is a first step toward a consistent integration of the impacts of demand response on the equilibrium outcome of power markets. However, conclusions come with some caveats. First, the integration of demand shifting requires an approximation to keep the model numerically tractable. Second, we are able to derive a first estimate for the energy efficiency supply curve, but its representation is stylistic and its quantification is based on a scant extant research. Thus, better data quality on potentials and costs of energy efficiency measures—and also with respect to temporal demand profiles and elasticities by sectors and regions—would lead to more precise results. Third, our framework captures only the effects of a partial equilibrium setting. Similar research should be conducted with frameworks that cover economy-wide effects (as done in Abrell and Rausch (2016) for transmission infrastructure). Fourth, we abstract from storage as another—in addition to gas power, transmission, and short-term demand response—major flexibility option and from investments in the ability to respond to prices in the short-term.

Chapter 4

The Gap Between Energy Policy Challenges and Model Capabilities

4.1 Introduction

The operation of energy systems has become increasingly challenging over the last decades for multiple reasons. First, the liberalization of energy markets has broken up vertically integrated structures to strengthen competition and lower supply costs. As a result, a variety of new stakeholders with different interests entered the energy system (Asane-Otoo, 2016). Second, renewable energy sources (RES) have increasingly been used to reduce greenhouse gas (GHG) emissions in the electricity sector, among other aims and benefits. Due to their intermittent nature, balancing supply and demand as well as preventing grid bottlenecks will require more short-term coordination between load, generation, and grid. The trend is set to continue in the future if the climate targets of the Paris Agreement are translated into legally binding rules and regulations. Meanwhile, energy systems are subject to developments in different sectors: electricity, heating, cooling, and transportation. A stronger integration of the sectors is essential to integrate high RES shares into the energy system and to lower GHG emissions in the heating and transportation sector (e.g., EC, 2016; Gerbonia et al., 2017). Thus, interdependencies between previously mainly decoupled subsystems will arise.[1]

As a consequence, the regulatory framework has to adapt to technological advances. For example, to handle the rising complexity of energy systems, grid operators are starting to rely on smart grids to balance load and supply. Moreover, smart markets[2] ensure an efficient allocation according to consumer preferences. Such technological advances change the system dynamics and require suitable regulations to ensure a level playing field for all stakeholders (Lo Schiavo et al., 2013).

In the same way, numerical energy system models have become more sophisticated and diverse with increasing complexity of real-world energy systems (Pfenninger et al., 2014). Despite their differences, many of the existing numerical models are used to answer similar questions. Models may provide different results, which lead to contradictory policy implications and recommendations. For example, some models see Power-to-X (PtX) technologies, that is, the conversion of electricity into other energy commodities, as an integral part for achieving national and international climate targets, whereas others hardly expect PtX in the energy system until 2050 (see Gerbert et al., 2018; Bründlicher

[1] This especially holds if policy-making targets at the cost-efficient reduction of total GHG emissions across sectors, where GHG emission reduction options are chosen according to their marginal abatement costs. This can, for instance, be achieved by integrating the heat and/or transportation sector into the European Union Emission Trading System (EU ETS).

[2] Within smart markets computational intelligence supports market participants by gathering as well as assessing information. Hereby, an improved (or even autonomous) decision-making within complex market structures, which would otherwise overwhelm the cognitive capacity of humans, can be facilitated (Ketter, 2014).

et al., 2017). In general, varying results can be caused by either different assumptions with respect to the development of technologies, or by differences in the general model structure. Moreover, due to a lack of transparency and standardization in the field of energy system modeling (Pfenninger et al., 2018), it is likely that some models might have been less suitable to answer specific research questions in the first place. We perceive this lack of transparency as a gap between the modeler's and the policy maker's perspective.

Consequently, policy makers should choose models, which capture the characteristics that are relevant for answering a certain policy question. Our work contributes to solving that problem by linking current energy policy issues to technical model requirements and thus closing the gap between modelers and policy makers. The method applied is based on the review and classification of the salient characteristics of a sample of energy system models and the clustering of energy policy issues. The considered models cover different regions of the world to provide a holistic overview.

We seek to increase the transparency between policy makers and modelers, which yields benefits for both: By linking policy issues with model characteristics, we identify crucial model components that are required to address specific policy issues. This information helps policy makers to assess the ability of models to answer specific policy questions without going into the technical details of models. In addition, the proposed methods can assist policy makers and modelers in identifying potential research gaps. If a lack of suitable models regarding an urgent policy issue prevails, policy makers might consider funding specific model enhancement. Furthermore, the linkage of energy policy issues with model characteristics will help modelers recognize their model strengths and weaknesses in relation to the questions they can answer compared to other state-of-the-art models. Our findings can also support energy modelers in tailoring their models to the underlying issue to avoid misspecified models.

This chapter sets a focus on models for power markets in the light of low-carbon policies. We follow a tripartite analysis, which is organized as follows: First, a classification system is developed that enables us to compare a large variety of model types while preserving a high level of detail with respect to model characteristics. To create a classification system that is capable of reflecting all relevant model specialties, a thorough review of existing approaches from the literature is conducted in Section 4.2. Building on this, we propose a novel model classification framework in Section 4.3 and apply it to a large sample of relevant energy models whose selection was validated by external modeling experts. Second, we develop a method to cluster the diverse issues with respect to the decarbonization of energy systems into a multi-level classification system in Section 4.4. For this purpose, the chapter reviews a range of publications and identifies key policy questions. Then, we link policy questions with the model characteristics. This is done by identifying the technical minimum requirements of models for a sample of energy policy questions to create an interface between the policy maker's and the modeler's perspective. Third, we develop a metric to measure the suitability of energy models for answering particular energy policy questions in Section 4.5. By applying the metric to our set of models and policy questions, we can reveal strengths and weaknesses of existing energy models. A second metric distinguishes between model features that are state-of-the-art and others, which are rather underrepresented in existing energy models. Finally, the chapter closes with conclusions and policy implications in Section 4.6.

4.2 Literature review

As described in the previous section, the population of models has become more heterogeneous with respect to the model specializations. Over the last few decades, the development of system tools for the modeling of energy issues has been seen as crucial (Urban et al., 2007; Nakata, 2004). In the following, we review literature on classification schemes for energy system models, which allows us to derive a classification fitting the linkage of model features and energy policy questions. The extant model comparison literature can be divided into four categories:

- *Category A* Creating an overview of models by describing the model structure and the conducted studies. (Focus: model description)
- *Category B* Creating an overview of models by developing a classification scheme either through the combination of existing schemes or through the introduction of new ones. (Focus: classification scheme)
- *Category C* Comparing models based on a classification scheme and identifying their field of use or rating them for different fields. (Focus: identification of field of use)
- *Category D*[3] Comparing models based on a classification scheme to identify a set of suitable models for a given issue. (Focus: identification of suitable models)

Almost none of the reviewed contributions contains elements of just one of these categories. Hence, a combination of categories is common, ranging from two to three categories per reference. Parts of the reviewed literature do not aim at the definition of a classification scheme. Therefore, we do not emphasize the main contribution of these works, but rather focus on the insights that are relevant to model classification approaches.

[3] This category may also be defined as a subcategory to C. Nevertheless, we want to distinguish between those two categories since the scope of Category C is much wider.

In summary, both, older and more recent literature, use a combination of criteria that are related to the structure and the underlying mathematical approach of the models as well as criteria that are related to the intended purpose and the field of use. We observed that the selection of these quantitative and qualitative criteria depends on the scope and goals of each individual work. Hence, older and newer contributions are equally important to the identification of a suitable model classification scheme. In the following, we present the literature in a chronological order,[4] sorted from the past to the present. Finally, Table 4.1 summarizes the key aspects of the literature review.

van Beeck (1999) presented a classification of energy models that aimed at local energy planning in developing countries. The author proposes a classification scheme to provide insight in the differences and similarities between energy models and thus facilitates the selection of the suitable energy models. A descriptive review of the (in their view) most relevant publications in the field of power market modeling is presented by Ventosa et al. (2005). A total of 36 models are categorized among three major trends: unit commitment optimization models,[5] market equilibrium models, and simulation models. Jebaraj and Iniyan (2006) published a broad overview of models as of 2005. It covers different types of models, containing energy planning models, energy supply-demand models, forecasting models, renewable energy models, emission reduction models, optimization models, as well as models based on neural networks and fuzzy theory. They identified important factors that are either incorporated in the objective function or as constraints and linked them to specific topics.

Möst and Keles (2010) presented a review and classification of stochastic models especially dealing with price risks in power markets. Moreover, the interaction between energy prices and technology choice are analyzed. In the same year, Connolly et al. (2010) analyzed 37 models (chosen and categorized based on a survey) according to their suitability to assess the integration of RES into energy systems. The models were categorized among their type and other characteristics, aiming to enable decision-makers at picking the most suitable model based on specific objectives. They distinguish the objectives by the type and scope of the underlying energy system, ranging from the analysis of a single generation unit up to the analysis of the whole energy system. It was shown that depending on the objective in place, different tools are most suited for the analysis. Bhattacharyya and Timilsina (2010) conducted a systematic comparative approach of

[4] The preferred order of sorting the literature would be "type of models analyzed" or "type of classifications used". Both sorting approaches are not possible, because no "type" of model can be determined without a universal classification scheme and the identified classification criteria overlap strongly.

[5] Ventosa et al. (2005) use the term "single-firm optimization models". In the context of other model classification terminology, this translates to unit commitment models for a single actor in the electricity sector.

ten energy system models. The purpose was the identification of suitable models to evaluate environmental policies of developing countries. They emphasized that most models are unable to capture certain aspects of developing countries such as non-monetary transactions.[6] Foley et al. (2010) described the changing role of electricity system models due to the unique requirements of liberalized markets. The trading of emission certificates and the rising share of RES were also identified as factors, which increase the complexity of the modeled system. Seven electricity system models are described in detail, providing information on which model is best-suited to analyze different aspects of the electricity system. Bazmi and Zahedi (2011), however, focus in their work mainly on the power sector and optimization techniques. They emphasized the effectiveness of modeling for policy makers in assessing different policies in the power supply sector. In Deutsch et al. (2011), several energy system models are compared in the context of energy scenario analyses. They concluded that further efforts are necessary for the definition of a suitable classification scheme.

DeCarolis et al. (2012) reviewed twelve models[7] with respect to their transparency. Their findings suggest that in most cases, the replication of model results is currently impossible. Timmerman et al. (2013) carried out a review to identify energy models suited for modeling the energy system of an industrial park. The energy model classifications were screened for adequate model characteristics and accordingly, a confined number of models was selected, and described. Pfenninger et al. (2014) analyzed models, which are known to be relevant for energy policy analyses. They identified four key model groups, namely energy system optimization models, energy system simulation models, power system and electricity market models, and qualitative and mixed-method scenarios, and categorized their models accordingly. For each group, key challenges were identified and development recommendations were proposed. Després et al. (2015) presented a detailed typology and applied it to compare five models with regard to their representation of power sector characteristics. Hall and Buckley (2016) proposed a model classification scheme to facilitate model comparison. Based on the UK model landscape and the appearances of models in the literature, 22 models were classified exemplary. Mahmud and Town (2016) did a review of computer tools for modeling electric vehicle energy requirements and their impact on power distribution networks. They reviewed 67 models to facilitate a selection of the most suitable tools for specific tasks. Olsthoorn et al. (2016) reviewed 15 models

[6] Shukla (1995) discusses the differences between modern western markets and markets of developing countries. In-kind payments are mentioned as an example for the "informal sector" of developing countries.

[7] DeCarolis et al. (2012) use the term "energy economy optimization (EEO) models". Subcategories of EEO models are defined as "computable general equilibrium (CGE) and technology explicit, partial equilibrium (TE/PE) models", whereas we would translate the TE models as "energy system models" in the context of this chapter.

Table 4.1: Overview of reviewed literature

Reference	A	B	C	D	Relevant goals or results
van Beeck (1999)	✓	✓	x	✓	Classifies models to identify the most suitable ones for local energy planning for regions experiencing rapid development.
Ventosa et al. (2005)	✓	✓	✓	x	Identifies power market modeling trends by classifying and characterizing the modeling approaches. Also makes qualitative statements for the strengths of those approaches.
Jebaraj and Iniyan (2006)	✓	x	✓	x	Identifies field of use for different types of energy system models.
Möst and Keles (2010)	✓	✓	✓	x	Overview and classification of stochastic models for price risks in power markets.
Connolly et al. (2010)	✓	x	x	x	Guideline on how to find the ideal energy tool for RES integration. Concludes that classifying by field of use is the most promising approach.
Bhattacharyya and Timilsina (2010)	✓	✓	x	✓	Reviews energy system models regarding their suitability for policy analysis in developing countries. Makes qualitative statements.
Foley et al. (2010)	✓	x	✓	x	Identifies suitable model approaches for the new challenges to liberalized markets.
Bazmi and Zahedi (2011)	✓	x	x	x	Summarizes literature regarding energy system modeling.
Deutsch et al. (2011)	✓	✓	✓	x	Compares models for scenario analyses and discusses the strengths of the models.
DeCarolis et al. (2012)	✓	x	✓	x	Enhances transparency of energy economy optimization model results based on their modeling approaches.
Timmerman et al. (2013)	✓	x	x	✓	Uses an existing classification scheme to identify the best suitable model for low carbon business parks.
Pfenninger et al. (2014)	✓	✓	✓	x	Identifies four key classification criteria out of the numerous existing classification schemes. Also rates the modeling approaches in regard to their suitability for current and future issues.
Després et al. (2015)	✓	✓	✓	x	Develops a new classification scheme applicable to both power sector models and long-term energy system models.
Hall and Buckley (2016)	✓	✓	✓	x	Systematic review of literature and policy papers since 2008. Compares all available energy system models with an appropriate classification scheme.
Mahmud and Town (2016)	✓	x	✓	x	Analyzes and identifies modeling tools for the integration of electric vehicles into the electricity grid.
Olsthoorn et al. (2016)	✓	✓	x	x	Compares existing computer tools for RES and storage integration and defines categories for the different models.

to integrate storage and RES into district heating systems.[8] Current modeling methods are further compared with respect to computational limitations, level of precision, and implementation of uncertainty.

This literature review serves as a basis for the development of a suitable model classification scheme for the purpose of creating the linkage between modelers and policy makers. A list including a summary of the reviewed literature and their respective allocation across categories is presented in Table 4.1. The model classification scheme, presented

[8] Although heating is not in the focus of our work, the models analyzed by the mentioned study mostly include energy system models, which are also used for analyses on the electricity sector.

in Section 4.3 is based on information from the literature belonging to both, Category A and B.

In Categories C and D, models are classified according to their field of use and/or to their specific issue. Thereby, they are regarded as static tools which are not subject to change. In contrast to these categories, the method we propose acknowledges that models evolve and can be used for different purposes. Similar to literature from Category A and B, we created a classification scheme, which can describe the model landscape transparently and based on their structure and most specific characteristics: the model features. Hence, the applicability of the models is based on the individual model features and not on the model as a whole, static entity. This makes our approach much more flexible since all models, which can be broken down to the set of criteria, we define in Section 4.3, can be easily included into our comparison.

4.3 Model comparison method

Within this chapter, a classification scheme for energy system models is developed. The aim of this framework is to provide a structured evaluation tool to facilitate the selection of suitable models for investigating specific research questions. The set of model comparison criteria is presented in the subsequent Section 4.3.1. The selection of models is described in Section 4.3.2. The evaluation is then applied in Section 4.3.3 within a two-step process, which comprises a first evaluation followed by a review to limit the human error.

4.3.1 Set of model comparison criteria

The extant literature offers several different sets of criteria to classify and compare energy system models (see Section 4.2). The criteria used range from technical descriptions of the model type to detailed model characteristics like the representation of specific power generating technologies. Nevertheless, to meet the challenges, which are present in current and future energy markets and to cover several issues connected to the future development, an adapted classification scheme is needed. We base our criteria catalog on the work of Hall and Buckley (2016) since this framework already contains most aspects that are relevant to capture the general structure of models. Yet, in contrast to Hall and Buckley (2016), the selection of criteria was expanded by a number of aspects to account for important issues with respect to future energy markets. The complete list of criteria is presented in Figure 4.1.

In this context, Pfenninger et al. (2014) formulated four structural changes for energy system modeling, including responsive demand, intermittent supply, distributed energy generation, and spatially varying potential of RES. These changes lead to the following challenges to energy system modeling: (1) resolving details in time and space, (2) balancing uncertainty, transparency and reproducibility, (3) developing methods to address the growing complexity of the energy system, and (4) integrating human behavior, social risks, and opportunities.

We grouped criteria into the main categories *model-theoretic specifications*, *detail of modeling*, *market representation*, and *general information*. Regarding the first one, *model-theoretic specifications*, we include three additional criteria compared to Hall and Buckley: "key endogenous features" of the model, the "representation of uncertainty and risk", and the "representation of acceptance". The set of endogenous variables mainly characterizes the adjustment paths resulting from a model since it is crucial to differentiate, which elements of the energy system are in its (partial) equilibrium state for a given model.[9] Hall and Buckley (2016) cover the aspect of uncertainty in a criterion describing the underlying methodology, for example, whether the model follows a stochastic approach. Nevertheless, representation of uncertainty and risk is included as an explicit criterion, which emphasizes its importance in line with challenges formulated by Pfenninger et al. (2014). A similar approach was applied by Cao et al. (2016), who introduced "uncertainty considerations" as an issue of their catalog. As of the representation of acceptance, it addresses the last challenge that Pfenninger et al. (2014) mentioned regarding the integration of human behavior, social risks, and opportunities.

Concerning the *detail of modeling*, an important issue addressed by Pfenninger et al. (2014) is the high penetration of electricity from intermittent RES, which results in the further need for energy system models with a high spatial and temporal resolution and an extended representation of flexibility options. Therefore, we describe the spatial properties not only by the spatial coverage of the modeled region, but also through the spatial resolution, which represents the granularity of the model. Moreover, different models might represent technologies and their respective costs at varying levels of detail. We captured these differences with the criteria "included costs" and "included technologies". In contrast to Hall and Buckley (2016), thermal generation technologies are mentioned explicitly, besides RES technologies and storage technologies. Since for many research questions a very detailed representation of those generation technologies is necessary, we further introduce the "details of thermal generation" and "details of storage modeling" as criteria. Examples for the former are partial efficiencies, cross-time-step restrictions or time-dependent availabilities, whereas the latter include the power capacity, the reservoir capacity, additional inflows, and storage losses. The necessity for analyzing single models with respect to these two criteria follows directly from the increasing market penetra-

[9] Partial equilibrium models are understood as models that cover only a strict subset of all sectors of an economy.

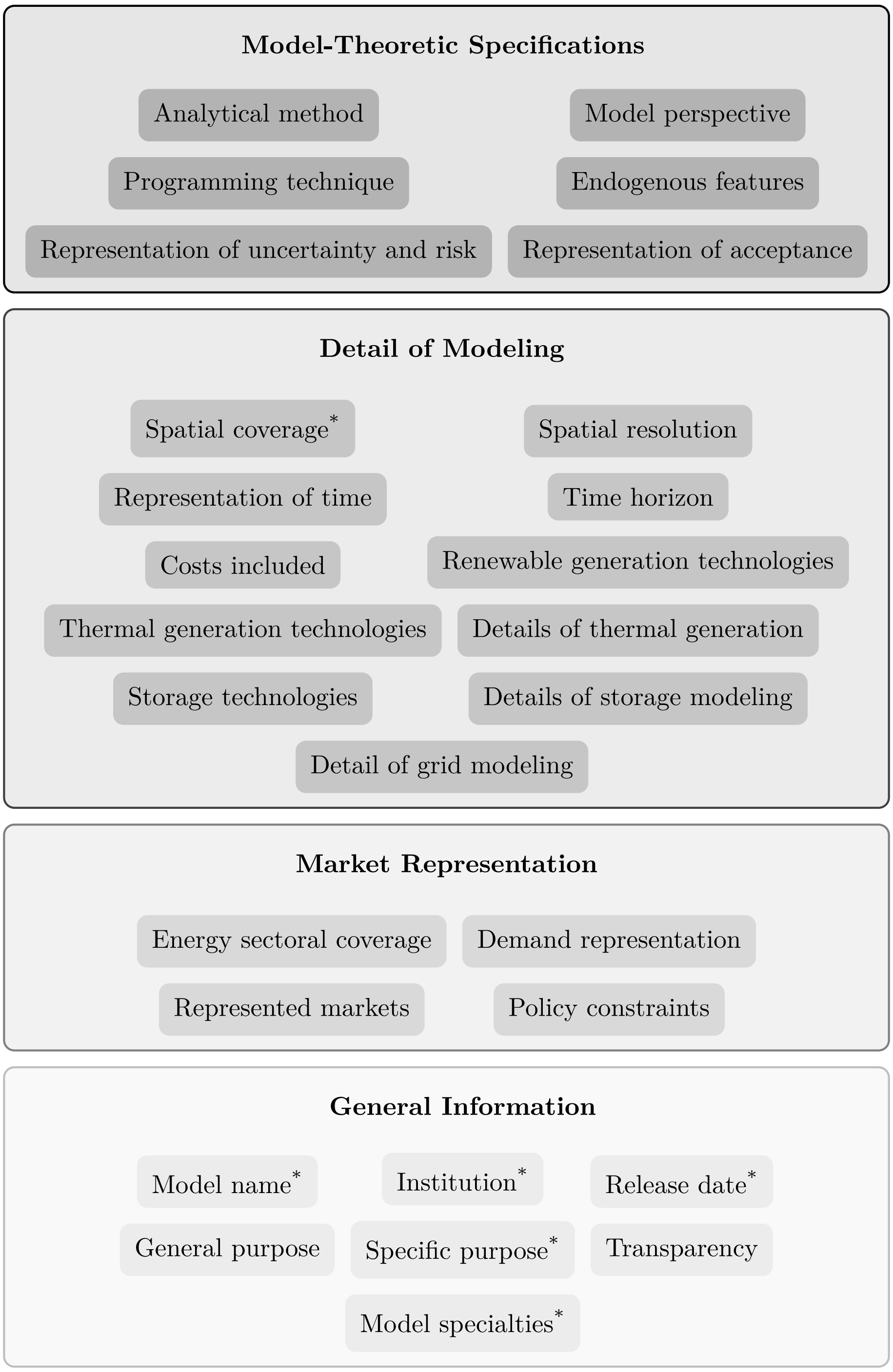


Figure 4.1: Model criteria grouped into the four main categories

Note: The criteria followed by an asterisk (*) correspond to open questions.

tion of intermittent RES, addressed above. The respective uncertain generation patterns result in increased flexibility requirements for dispatchable generation technologies. Another criterion in this section is the "represented detail of grid", as also applied by Després et al. (2015). Whereas stylized energy market models might not incorporate the grid at all, for other approaches, as dispatch models or congestion modeling, a high resolution of the grid with differentiation between DC and AC load flows might be necessary. Additionally, this aspect is also relevant for representing the growing complexity of the energy system (Pfenninger et al., 2014).

For the *market representation*, besides energy "sectoral coverage" and "demand" representation (Hall and Buckley, 2016), we include "policy constraints" to analyze whether the models are able to include policy instruments like emission constraints or quota for RES. A similar approach was applied by Bhattacharyya and Timilsina (2010), who grouped models with regard to their capability to analyze price-induced (e.g., feed-in tariffs) or volume-induced policies (e.g., technology quotas). Furthermore, we evaluate models according to the "represented markets": spot markets, future markets, balancing markets, and capacity markets. On the one hand, this is again motivated by the increasing relevance of auxiliary services to facilitate the integration of RES. On the other hand, the well-known missing money problem in power markets induces the importance of additional revenue sources for generation assets (Hogan, 2017).

Finally, we also collect the *general information* on models within this analysis. Compared to Hall and Buckley (2016), we added two criteria, namely "transparency" and "model specialties". The transparency of a model is defined as the availability of the model to the public with respect to the source code, the used data, as well as the description of all equations. Yet, due to limited transparency of models and, in addition, the difficult interpretation of publicly available information in the context of the rising complexity of models, information on the validation of models might be more useful in the end. Similarly, Pfenninger et al. (2014) address the "issue of validation" of energy system models, due to a widespread lack of transparency and/or accessibility. A comparable criterion was implemented by Connolly et al. (2010). Moreover, the importance of transparency was further emphasized by Cao et al. (2016), who developed an extensive "transparency checklist" to guide authors of energy scenarios to a higher level of transparency.

The "model specialties" are an uncommon criterion in the literature so far. It is intended to describe properties and applications of the model, which are unique or distinguish it from other, similar models, and thus helping to identify suitable models for specific research questions. Yet, the criteria that belong to this category are not considered in the comparison of model capabilities that is conducted within this chapter. The information on general properties is rather collected for reasons of transparency and documentation.

4.3.2 Sample of analyzed models

For the purpose of this chapter, a sample of 40 energy system models was chosen.[10] The aim was to find a suitable set, covering a high diversity of different regions[11] and applications (e.g., simulation or optimization models), and including a large fraction of the most popular models applied in the literature. This analysis looks exclusively at large-scale (i.e., great number of constraints), numerical, partial equilibrium models. Hence, we neglect analytical models that allow for deriving equilibrium conditions or even closed-form solutions without the quantification of parameter values. Yet, the high number of applied energy system models and varying availability of model characteristics hardly allow for an objective selection of models. Hence, we selected models by means of a sequential process. At first, we compiled a list of around 50 well-known and applied energy system models. In a second step, a group of external experts[12] provided feedback on this list, which was then used to define the final sample of models that is shown in Table D.1 in Appendix D.1. The models were analyzed with respect to their characteristics based on the information available as of March 31, 2017.

4.3.3 Evaluation and results

The set of criteria presented in Section 4.3.1 are based on either multiple-choice questions (if the number of possible answers is below ten) or open questions. Among the multiple-choice questions, some are by definition binary, whereas others have several possible answers (the different options for multiple choice questions can be found in Appendix D.2). Thus, the criteria can be regarded as subcategories including one or several model features. To improve the processing of information, the different options in the case of multiple-choice questions are listed separately and a binary evaluation is applied to them. A "yes" means that the model or the modeling framework has the feature (or is able to include it if it is provided in the data), whereas a "no" means that the feature cannot be included without extending the model. All criteria are analyzed by means of

[10] For model frameworks, an existing model was chosen to make the comparison possible.

[11] Twenty-five models and model frameworks (62.5%) focus on regions within Europe only. Of the remaining, at least twelve (30%) have been used for developing countries. There are six models (15%) with a global coverage.

[12] We want to thank Paul Deane, Steven Gabriel, Rolf Golombek, Josiah Johnson, and Katrin Schaber for providing us with very valuable feedback on the list of models. More precisely, we asked the experts the following two questions with respect to the initial sample of models: "Are there models missing that play an important role in energy-system modeling at the moment?" and "Does the list contain models that are outdated and do not represent the current state-of-the-art methodology?". The expert opinions only led to additions to the list of models.

the publicly available information on the respective model (see references in Table D.1 in Appendix D.1).[13]

Results indicate that among the 40 analyzed models, it appears that all of them are able to model the most common conventional and RES power plants, consider pumped-hydro electric storage, model the transmission grid at least as a transportation problem, and are able to provide the dispatch of the generators and the storage as key endogenous features. Apart from some exceptions, most of the models have a spatial resolution higher than ten regions/nodes and a temporal resolution of at least one hour. Models vary with respect to the range of unconventional technologies they model (CCS, tidal/waves, battery and hydrogen storage, etc.), the details of thermal generation modeling, the sector-coupling capabilities, the policy constraints they can include, and the markets they can represent. These aspects, in addition to the key endogenous features, reflect the specialties of the models. Almost none of the models considered here were able to model public acceptance, nor are they usually used to depict the distribution grid.

This section introduced our approach for analyzing a sample of models with respect to the criteria presented. The subsequent section aims at the policy side of this chapter and hence translates a selection of energy policy questions into subsets of our model comparison criteria.

4.4 Energy policy issues cluster

This section aims at highlighting the policy maker's side of the gap introduced in Section 4.1. The previous section described the methodology for analyzing energy system models. To characterize the policy maker's side, an analogous method has to be adopted for energy policy issues. Hence, this section designs a framework for the categorization of energy policy issue, which captures the broad variety of current energy policy. It will be applied to select energy policy issues of different categories that will be then used for a model assessment. Our approach for this section comprises three steps. First, we describe the method for the categorization of issues and their terminology. Then, we highlight some of the identified categories (a complete description of all categories can be found in Appendix D.4). At the end, we link exemplary policy issues to model requirements.

The common focus of all reviewed energy system models is the electricity sector. Thus, in this chapter, only a subset of energy policy issues is taken into account for the description of the policy maker's side. The approach for defining the scope of issues includes the review of existing publications that analyze paths for the decarbonization of energy

[13] See Appendix D.3 for an example of a model analysis.

markets. A variation of the scope either on the modeler's or the policy maker's side is of course possible.

4.4.1 Method and terminology of the energy policy issues categorization

The process of characterizing current major energy policy issues consists of three steps. First, a literature review is conducted to gather keywords related to energy policy issues. Therefore, existing model-based analyses on energy policy questions have been reviewed.[14] The review includes the extraction of keywords describing the energy policy issues addressed by a publication. Second, similar keywords from the first step are clustered together in such a way that they can be easily connected to model features. This model-oriented clustering approach leads to the *Energy Policy Issues Cluster* (EPIC) depicted in Figure 4.2. This novel approach allows us to bridge the existing gap between modelers and policy makers. Last, we formulated twelve research questions which are presented in Table 4.2 that capture one or multiple energy policy issues.[15] The assessment of models (see Section 4.5) is based on their capability of answering those questions.

The EPIC consists of different components, which are described in more detail in Section 4.4.2. A research question addresses one or multiple *energy policy issues*, where issues have three dimensions: the *object dimension* (gray columns in Figure 4.2), the *evaluation perspective dimension* (dark gray rows) and the *framework conditions* (light gray background). The first dimension refers to the possible model extensions, whereas the second dimension can be interpreted as the observed outcomes. Moreover, the object dimension can be further split into *instruments* and *energy system design*. The individual columns and rows in the cluster are the issue *categories*. A specific policy issue is located at the intersection of two categories.

4.4.2 Description of the cluster

The EPIC is developed to derive model requirements from energy policy issues. Modelers can derive model requirements for specific research questions, but this information is not generic enough to transfer it to other research questions. The cluster is designed in such

[14] More precisely, we reviewed 97 publications of public and private research institutes with a technical and/or economic focus. Publication dates start from 2009 on to capture the most recent energy policy issues. All publications include a model-based analysis with energy system or energy market models, which at least comprise the electricity sector.

[15] The research questions are exemplary questions selected to represent the variety of issues captured by the EPIC. They do not necessarily describe research question actually tackled in the reviewed publications. However, because they are derived from keywords of recent publications, they still represent the current issues.

a way that policy makers and modelers can easily identify the core components of any given research question. This allows both sides to identify suitable model configurations for any research question. The following paragraphs will describe the EPIC, which is depicted in Figure 4.2.

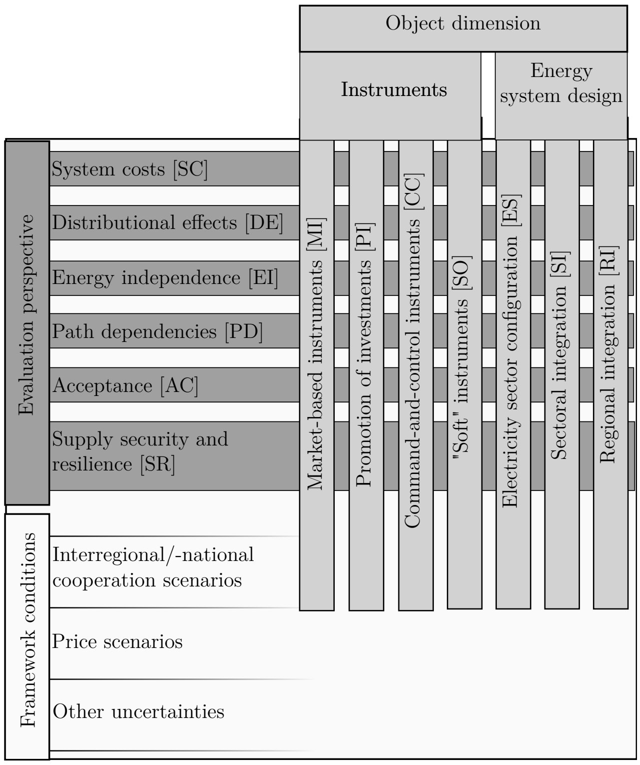


Figure 4.2: Energy policy issues cluster (EPIC)

Object dimension The object of an issue is the element being analyzed. We identified two major types of objects: instruments and energy system design. On the one hand, energy system design describes the structure of the analyzed energy system at fixed points in time. Instruments on the other hand, describe the regulatory options that affect the development of energy systems. We will first describe the instruments and then the energy system design in the following.

The categorization of instruments is based on a structure used by Fais (2015) and Beestermöller (2017). Although various other categorization schemes exist in the literature, some of them do not cover all the relevant instruments (see Batlle et al., 2012) or utilize a structure that is less compatible to the one of energy system models (see Mickwitz, 2003; Böcher, 2012).

The main concept of our model-oriented clustering approach can be explained by means of the following example with the keywords *tax incentives for RES* and *volume-controlling instruments* (e.g., EU ETS). Both belong to the instruments of the object dimension, but are assigned to different categories. Similarly to Beestermöller (2017), we assigned *tax incentives for RES* into the category *promotion of investments* because those instruments are modeled as reduced investment costs and therefore influence the economic attractiveness of certain technologies. The EU ETS is a *market-based instrument* and is treated in a different way by models. One way for modeling the EU ETS market in linear bottom-up models would be the introduction of an additional CO_2 constraint. Thus, the inclusion of this type of feature aims not at the input side of the model, but rather on the set of its constraints, which clearly distinguishes it from tax incentives. The presented categorization scheme is designed to fit different model types.

The second type of object categories is the energy system design. This group focuses on the technical aspects of the energy system. Research questions such as "Can the integration of the heat sector provide the flexibility, which is needed in a highly decarbonized energy system?" can be assigned to this type of objects. Our literature review resulted in the following object categories: "Electricity sector configuration", "Sectoral integration", and "Regional integration". Similarly to the instruments, these categories are chosen while having the structure of energy system models in mind. Additional sectors and the regional perspective require a different set of equations and adjustments to the resolution (e.g., the number of regions). Those categories are easily identifiable in research questions as well as in the model structure. Therefore, topics regarding the electricity sector configuration, further energy sectors, and the regional integration can be grouped into one of these three categories.

Evaluation perspective The upper horizontal rows of the cluster (see Figure 4.2) describe the evaluation perspective. We use the same understanding for the terminology of "evaluation perspective" as in PSC (2008):

> The subject of an evaluation [...] may be [...] a system [or a] policy [...]. Evaluation perspectives point to the main focuses of an evaluation.

The majority of models comprised in our sample minimizes the total system cost of the modeled electricity system and thus usually provide results affiliated to the evaluation perspective "system costs".[16] These kind of models are not limited to this category and hence can be used for other evaluation perspectives as well.

Framework conditions The framework conditions can be interpreted as a third dimension intersecting with each energy policy issue. For simplicity, they are depicted as a light gray background in Figure 4.2, which is present at every intersection. We found

[16] Note that the objectives of cost minimization or welfare maximization lead to different objective functions, yet, in the case of inelastic demand, the outcomes are equivalent.

that framework conditions have a high impact on the number of required model runs, but little connection to the model requirements. An exemplary issue assigned to the group *framework conditions* could be the analysis of different price scenarios. A modeler would interpret this problem as an input parameter variation, hence it has no particular model requirements. Nevertheless, the analysis of different price scenarios is, for instance, a common keyword found in the reviewed literature. We conclude that energy policy issues containing additional framework conditions do not impose additional model requirements.

Table 4.2: Overview of analyzed research questions

	Research Question	Issues
Q_1	Which cost-optimal charging strategies guarantee a safe operation of the electricity grid?	ES.SC; ES.SR; SI.SC; SI.SR
Q_2	What is the cost-efficient technology-mix (e.g. investment in energy efficiency, sector coupling, renewable-based heat supply) for decarbonizing the heat sector?	SI.SC; SI.SR; SI.EI
Q_3	Can heat storage units provide large-scale bulk electric storage in the future?	SI.SR; SI.SC; ES.SR; ES.SC
Q_4	What are the impacts of smart grids on the conventional market structure?	MI.SC; RI.SC; SI.SC; MI.SR; RI.SR; SI.SR
Q_5	How should sector-specific CO_2 targets be defined to minimize CO_2 abatement costs?	CC.SC; SI.CC
Q_6	How much can distributed RES generators (especially wind and PV) contribute to firm energy in energy systems with high shares of RES?	RI.SR; RI.EI; ES.SR; ES.EI
Q_7	What is the effect of zonal pricing on the location of new power plants and re-dispatch costs?	MI.DE; MI.SC; ES.SC
Q_8	What are the consequences of an increasing share of prosumers on the different levels of the grid infrastructure?	RI.SC; RI.SR
Q_9	Which lock-in effects can result from investment incentives in specific technologies in the heating sector?	PI.PD; SI.PD
Q_{10}	How does the share of self-consumption, support scheme and technology costs impact new investments into decentralized technologies?	PI.PD; PI.DE; SI.PD; MI.DE; MI.PD; ES.PD
Q_{11}	What is the long-term effect of an incomplete utilization of the energy efficiency potential due to overestimated effects of voluntary obligations and information policy?	SO.PD; ES.SC; RI.SR
Q_{12}	How does the cost-optimal grid expansion deviate if acceptance is taken into account?	ES.SC; ES.AC; ES.SR

The analyzed research questions and their location in the EPIC can be found in Table 4.2. We validated the completeness of the cluster through a literature review and expert opinions.[17] As an example, the work of Fischer et al. (2016) has been used to test the cluster. They identified the five most pressing energy-transition-related issues of Germany by analyzing stakeholder workshops, surveys and keyword searches of academic literature.

[17] We want to thank Alexander Zerrahn (DIW Berlin, research associate, energy and environmental economics) and Philipp Kuhn (Technical University of Munich, lecturer, energy system modeling) for their expert opinion on the energy policy questions introduced in this section.

Four of them, which required quantitative analyses of electricity system models, can be located within the EPIC.

4.4.3 Policy questions analysis

Finally, the same criteria as in Figure 4.1 are now combined with the research questions listed in Table 4.2 to determine the importance of a particular model feature for answering each of these questions. For that purpose a two-step process involving a first evaluation and a review was adopted. Furthermore, the evaluation of features distinguishes between three levels of importance:[18]

- *Mandatory features* are the model features required in a minimalistic model that can provide an acceptable answer to the policy question.
- *Complementary features* are the model features that can complement the model, but whose absence does not alter the results too much in regard to the given policy question.
- *Facultative features* are the model features that do not affect the results in regard to the given policy question (or only affect them marginally), and can therefore be ignored.

For most of the policy questions listed in Table 4.2, the evaluation showed that the generation and storage dispatch (endogenous features), the storage characteristics (charging/discharging capacity and storage capacity), RES generation technologies (photovoltaics, wind, biomass), batteries, and costs (investment, fixed, variable, fuel) are usually mandatory features. This is not surprising, as many policy questions address the challenges to integrating variable RES generation while maintaining some flexibility.

The set of facultative features comprises some endogenous features (technological learning, market prices, emission rates and prices), some represented markets (capacity markets, futures), some policy constraints (CO_2 budget, RES quota), details of storage modeling (additional hydro inflow), and two renewable generation technologies, namely wave and tidal. There are several reasons why these features were usually considered optional. First, the endogenous features, the represented markets, and the policy constraints are “special” features that are only needed in particular case studies. This correlates with the observation made in Section 4.3. Only a few models have implemented them, thus they reflect the specialties of the models. Second, a shift of interest from conventional energy storage technologies (hydro) to batteries might be the reason behind the lack of interest in modeling the additional hydro inflow. Third, technologies that currently have

[18] See Appendix D.3 for an example of a policy question analysis.

a negligible contribution to the power system such as wave and tidal can be ignored in most policy studies, unless they are the focus of these studies.

All in all, most features tended to one of the three levels of importance (mandatory, complementary, facultative), and only a few features were evenly split between them. This highlights the need for a variety of models to answer a wide range of policy questions with different requirements. Whether the models are able to cover the whole range will be discussed in the following section.

4.5 Closing and quantifying the gap

After presenting the model comparison method in Section 4.3 and the EPIC in Section 4.4, the next step is to link the models and the energy policy issues with each other. With the creation of this linkage, we close the gap between the modelers and the policy makers. Two metrics are introduced to quantify the gap between models and policy questions. The results are then discussed and discrepancies between the models and the policy questions are identified.

Since only a small set of policy questions and a limited number of models is analyzed, the conclusions from this section cannot be generalized. However, the underlying method for creating the linkage and quantifying the gap can be applied to a wider range of models and questions. The main purpose of this section is therefore to illustrate this method, which can be applied by policy makers and modelers.

4.5.1 Linkage and gap quantification

Section 4.3.3 analyzed the capabilities of the models, whereas Section 4.4.3 gave an insight on which features are required to answer certain policy questions. The purpose of this section is to link the models to the policy questions and determine whether they fulfill the requirements for answering them. Therefore, a metric is introduced to quantify the gap between each model m and each policy question q. The *model-question gap* $d_{m,q}$ is defined as follows:

$$d_{m,q} = 1 - \frac{2 \cdot |S^q_{++} \cap S^m| + |S^q_{+} \cap S^m| - 2 \cdot |S^q_{++} \cap \overline{S^m}|}{2 \cdot |S^q_{++}| + |S^q_{+}|} \tag{4.1}$$

where S^q_{++} denotes the set of mandatory features for a question q, S^q_{+} the set of complementary features for a question q, S^m the set of implemented features in model m, and $\overline{S^m}$ the features that are not available in model m.

There is no gap if the model has all mandatory and complementary features ($d_{m,q} = 0$). The gap widens greatly if mandatory features are missing (hence the term $-2 \cdot |S^q_{++} \cap \overline{S^m}|$), and to a lower extent if complementary features are not implemented. The largest possible model-question gap ($d_{m,q} = 2$) occurs when neither mandatory nor complementary features are available in the model. Note that a sophisticated model with a great number of features has no advantage over a simple model, which fulfills the requirements for addressing the policy issue, since both of them have a model-question gap close to zero.[19]

Besides the model-question gap $d_{m,q}$ that can be used to assess the suitability of a model for answering a policy question, another metric can be applied to the data to find out the key features that are not widely implemented. This *feature gap* can be defined as follows:

$$d_f^{M,Q} = \frac{\sum_{q \in Q} |S^q_{++}(f)|}{|Q|} - \frac{\sum_{m \in M} |S^m(f)|}{|M|} \tag{4.2}$$

where $d_f^{M,Q}$ is the feature gap for a given set of models M and policy questions Q. The first term in the subtraction can be interpreted as the average importance of feature f for answering the policy questions, whereas the second term is the average occurrence of feature f in the models. The gap is zero if there are enough models that include the feature f given its importance for the policy questions. If it is negative ($-1 \leq d_f^{M,Q} < 0$), then the share of models implementing f is higher than the share of policy questions that consider it as important. The last case, where $0 < d_f^{M,Q} \leq 1$, is the most relevant for this study. It highlights the discrepancy between the significance of a feature for a set of policy questions and the limited number of models including it.[20]

4.5.2 Results and discussion

Equation (4.1) was first applied on the set of models from Table D.1 (see Appendix D.1) and policy questions from Table 4.2. The performance of the models varies widely for the given set of questions, with the most suitable models achieving gaps as low as 0.02, whereas the worst-case featuring a gap value of 1.18 (see Figure 4.3). Looking at each model separately for the whole set of policy questions, it appears that some models are well-suited for all questions with an average gap of 0.09, whereas others, with an average gap of 0.92, are not suitable for answering any question. These results are a clear reminder that modelers should be very cautious when choosing an existing model to answer a policy question. Likewise, policy makers should not take the suitability of models for granted.

---

[19] See Appendix D.3 for an example of the model-question gap quantification.

[20] See Appendix D.3 for an example of the feature gap quantification.

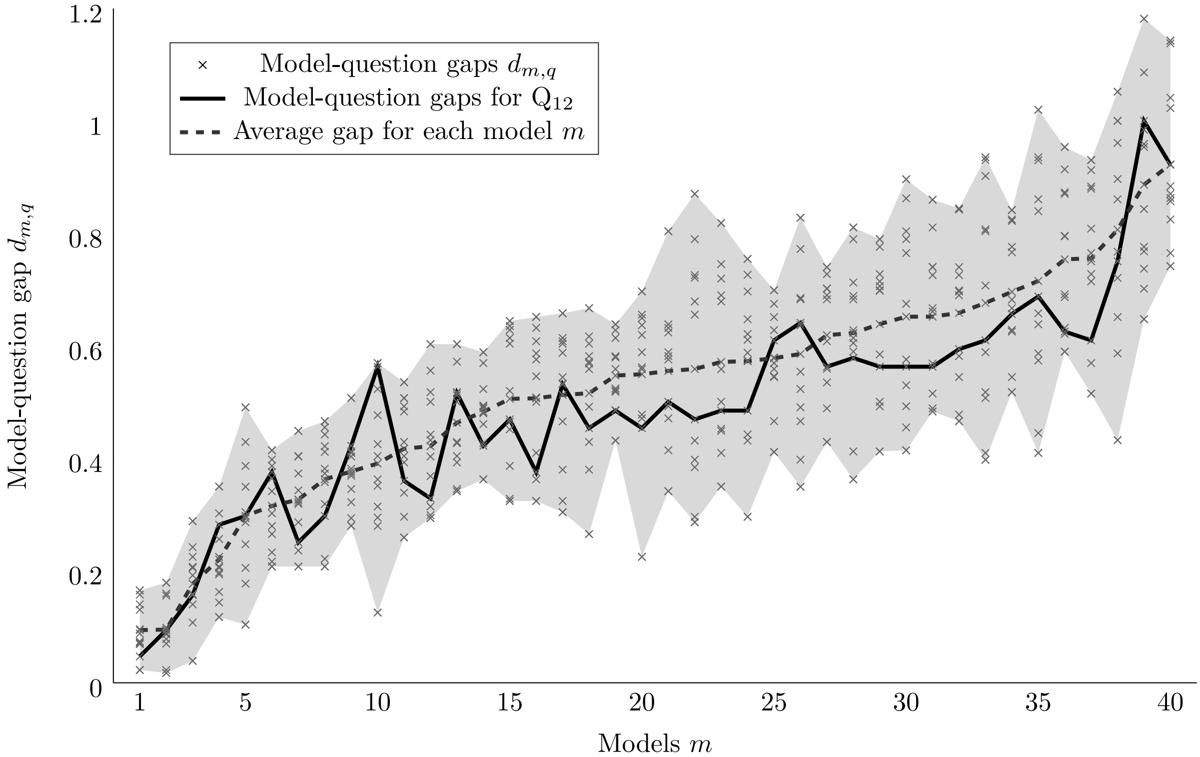


Figure 4.3: Model-question gap for sample of models

Note: The model-question gaps $d_{m,q}$ are displayed for all analyzed models and policy questions, so that there are twelve gray crosses aligned vertically for each model ID in the horizontal axis. The models are anonymized and sorted by their average model-question gap for the given sample of questions. The gap is low (close to zero) if the model contains most mandatory and complementary features, and is high (up to two) if these features are missing. For the sake of illustration, the model-question gaps are shown for the question Q_{12} (black line) as well.

It should be noted that the best-performing models might not be suitable for answering questions outside of the set in Table 4.2, and that the worst-performing ones might have been designed for other purposes.

Nevertheless, the set of policy questions covers a wide range of issues, and the results reveal the strengths and weaknesses of the models. The difference between the smallest and the largest gap for a given model m could be as high as 0.62, and is on average 0.37. This could be explained by the existence of highly specialized models that have a small gap for only one or two questions and which tend to perform badly for the rest. Assuming that the policy questions are representative for the policy issues they belong to, the link between the models and the issues they specialize in can be established.

The feature gaps for the same sets of models and policy questions show that there are at least four groups of features that are under-served in the chosen models. The complete results are available in Figures D.5 and D.6 (see Appendix D.5). An excerpt is reported in Figures 4.4 and 4.5.

The largest discrepancies are related to the modeling of (electric) distribution grids ($d_f^{M,Q} = 0.28$) and, more broadly, of the load flows ($d_f^{M,Q} = 0.23$) (see Figure 4.4). Especially the former is missing in most models, with only two models capable of incorporating distribution grids. One possible solution would be to encourage modelers to implement these features (i.e., through targeted project funding). However, limited computational capacities and lack of reliable data on the distribution level might be the reason behind the absence of the features in the first place. The alternative, which is probably applied by modelers who attempt to answer policy questions requiring these two features, is to couple their models with detailed load flow models with both the transmission and the distribution grid. Thus, to alleviate this discrepancy, data on distribution grids needs to be made available or to be created generically, and methods to increase the computational performance of complex models and to couple them with load flow models need to be explored.

The second group of features where discrepancies have been observed is related to the modeling of the demand as an endogenous key feature ($d_f^{M,Q} = 0.03$) and, more importantly, to the long-term demand flexibility modeling ($d_f^{M,Q} = 0.14$) (see Figure 4.4). These features are of paramount importance when modeling future scenarios with sector-coupling, yet most analyzed models are still lagging behind in this regard.

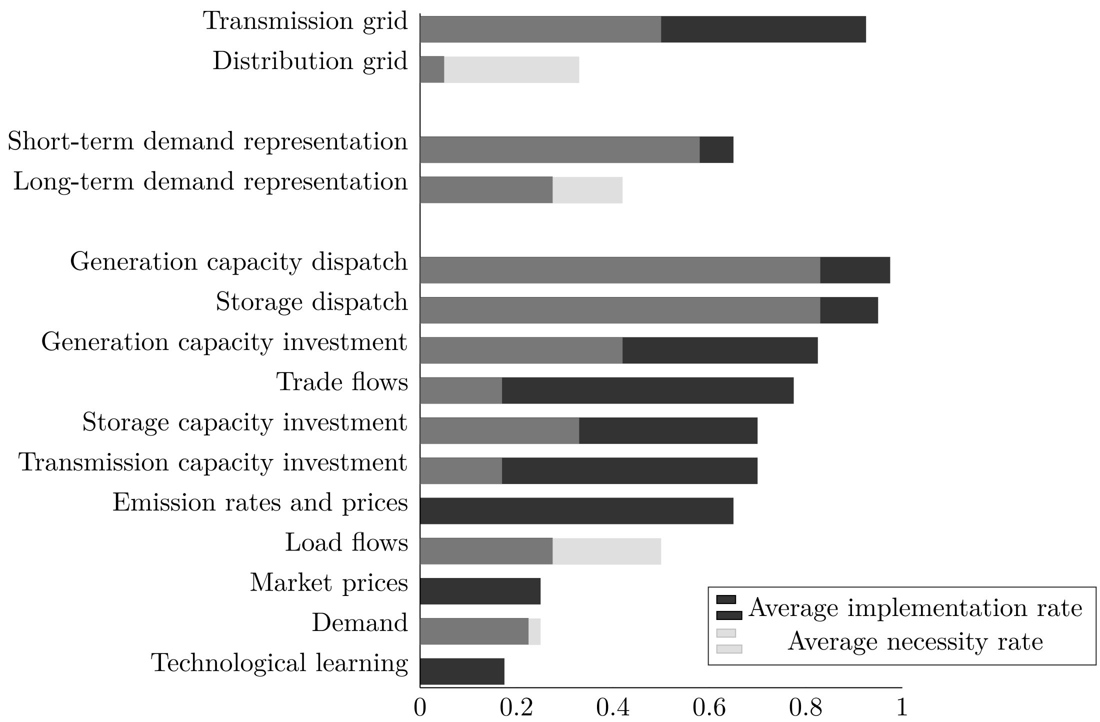


Figure 4.4: Average implementation rate and average necessity rate for the features related to grid and demand representation

Note: The bars are superposed, so that the black bars are only visible if the implementation rate exceeds the necessity rate. Otherwise, critical discrepancies exist and are colored in light gray.

The third group of features concerns the technical flexibility of the energy system (see Figure 4.5). Only 45% of the analyzed models include batteries as a storage technology, even though 67% of the chosen policy questions require this feature. There is also a high demand for models that include the heat sector and that are capable of investigating the power-to-heat potential. Moreover, the flexibility of conventional power plants needs to be assessed more accurately through the modeling of operational costs such as ramping costs and start-up costs ($d_f^{M,Q} = 0.10$). Here again, the computational performance is probably the reason behind the lack of these features. While this is expected to improve over time, one possible solution in the short term would be to rely on specialized models (for the heat sector, or for the unit commitment) and couple them with more general models.

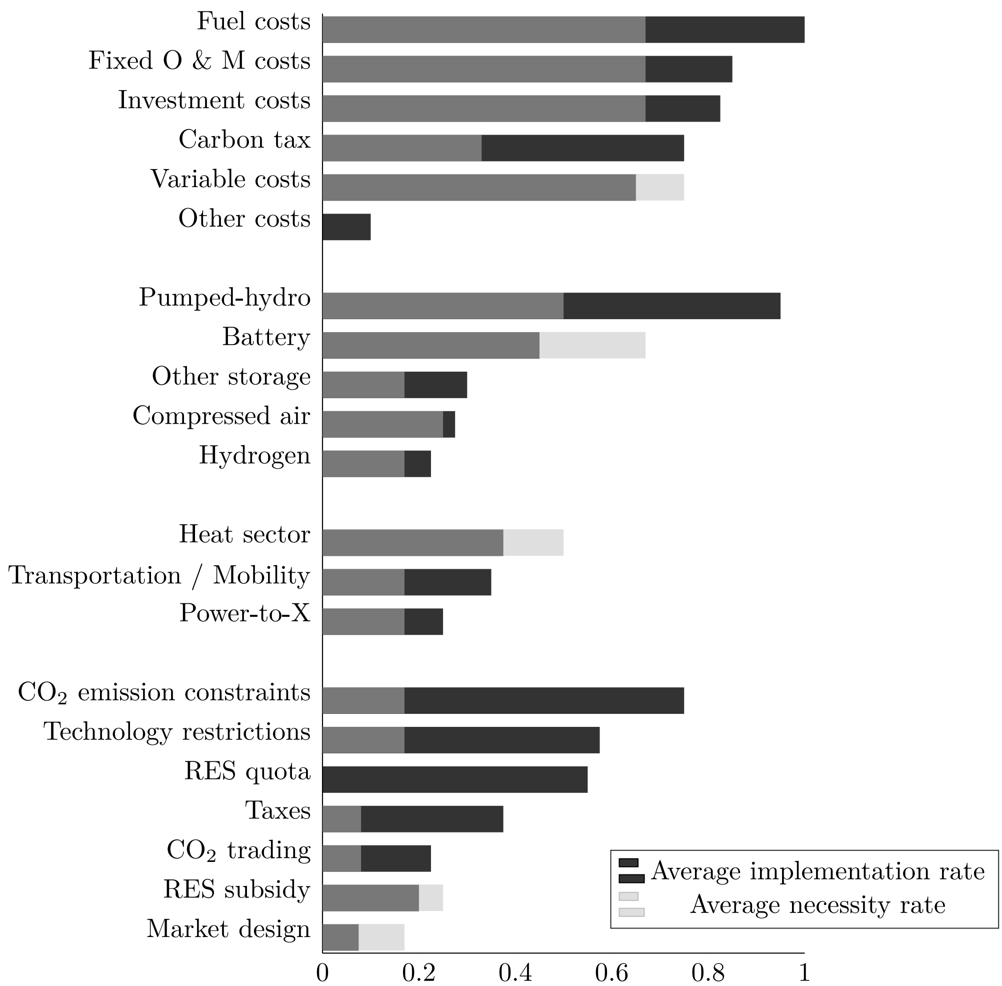


Figure 4.5: Average implementation rate and average necessity rate for the features related to costs, storage, sector coupling, and policy constraints

Note: The bars are superposed, so that the black bars are only visible if the implementation rate exceeds the necessity rate. Otherwise, critical discrepancies exist and are colored in light gray.

Models not only need to include more flexibility features, they also have to implement more policy constraints such as market design ($d_f^{M,Q} = 0.09$) and RES subsidies ($d_f^{M,Q} = 0.05$). The demand for these features reflects the evolution of policy concerns and the trends in the energy systems where more market participants are expected, where conventional market structures are disrupted, and where policy makers make use of subsidies to reach certain emission targets. While the RES subsidy is comparatively easy to implement, the market design constraint might lead to a rethinking of how the markets are modeled in the first place.

The feature gap should not disguise the fact that there are always models capable of using any of the identified features. The metric is based on the simple idea that if there are more policy questions requiring a feature, there should be also more models implementing it. However, this quantitative approach does not guarantee that the features are well implemented in the models. Besides, a couple of suitable models might be enough to compare the results and make robust policy decisions. Nevertheless, we believe that the existence of a high number of models implementing a feature will lead over time to the emergence of qualitatively good model assessments.

4.6 Conclusion and policy implications

The transition towards a low-carbon and efficient energy system requires a regulatory framework, which sets the right incentives for stakeholders to align their behavior with the desired energy system. Due to the liberalization of energy markets and the coupling of energy sectors, the number of stakeholders and system operation constraints has increased, leading to an increasingly complex system. To support policy makers, a wide range of numerical models have been developed over the last decades.

The primary goal of this chapter is to provide policy makers and energy modelers with a method on how to identify suitable energy system models for their policy research questions. Besides, our approach can be used to quantify the research gap, that is, the model extensions required to gain adequate insights for a given research question. One further goal is to help modelers benchmark their energy system models with other state-of-the-art modeling approaches and adapt them to the research question requirements.

Starting from an extensive overview of studies on energy system model comparisons, we derived the conclusion that the existing studies use different terminologies and classification schemes that can be restricted to certain model types. Building on the existing studies, we identified model characteristics, which are relevant for both, modelers and policy makers. Then, we applied the comparison scheme on a set of 40 wide-ranging models. All in all, the model characteristics were sufficient to distinguish the models and to highlight their key features. However, the comparison scheme does not include any weighting between the criteria nor any qualitative ones (features are equally weighted). So-called model frameworks or model generators can only be compared if an actual model is considered, otherwise the results will be skewed in their favor due to their expandability. Most of the difficulties faced during the comparison process are caused by a lack of transparency in the model descriptions. To ensure the comparability of the models, which is a necessary condition for the comparability of model results, we recommend that policy makers and funding institutions include the model transparency as a condition for project funding. Documentation standards are also necessary and should comprise the model capabilities, in a single model run, objectively.

In a second step, we looked into energy policy classification studies. To the best of our knowledge only a few such studies exist, and they sometimes used a terminology specific to their field, which limits their usefulness for energy system modelers. Therefore, we developed a novel, model-oriented clustering method for energy policy issues. Our method decomposes complex policy research questions into several, distinct energy policy issues. The object of the research question and its perspective are defined with a model-oriented approach that establishes connections to inputs, constraints, and outputs. Then, this clustering method was applied to derive twelve exemplary policy questions. However, the set of questions presented in this chapter is only related to power market models, with a focus on decarbonization-related challenges. Based on a wider range of policy questions, the proposed cluster can be expanded to include additional environmental aspects, issues related to resource limitations, and effects from global warming, just to name a few. Besides, the method can be applied to other energy system models (other than power markets).

To link model features with policy questions, we introduced two simple metrics, which quantify the model-question gap and the feature gap. The analysis of the model-question gaps highlighted the importance of choosing suitable models for each question, because some models lacked the critical features for answering certain policy research questions, which might lead to inaccurate results and unsubstantiated policy recommendations. The results could also be used to identify the model specialties in terms of policy questions. Looking at the individual features separately, it appears that critical features for policy questions are usually implemented in most models. However, feature gaps exist in these four areas: distribution grid modeling, endogenous demand modeling, technical flexibility of the energy system, and policy constraints. Despite the useful insights obtained through the two metrics, some limitations exist. In fact, the method is purely quantitative and does not include any qualitative aspects. It is also subjective, because the results are based on the opinion of modelers, even though this aspect has been minimized through internal review processes. The conclusions are restricted to the sets of models and policy questions and should not be generalized. General assertions can only be achieved through a wider range of models and policy questions.

The major contribution of the chapter, besides the linkage between policy issues and model features, is guidance with respect to the choice of appropriate models. We recommend applying this method in a selection process, where a variety of models are at the disposal of modelers or policy makers. In this case, the model-question gap metric (see Section 4.5.1) could be applied to either define a threshold value or evaluate the gap between a model and the particular policy questions. Moreover, we are able to identify some need for action with respect to future model developments. Either funding entities or research institutes should use our insights to initiate new tenders or revise their research agenda, respectively. The feature gap, as it was introduced in Section 4.5.1, allowed to identify four model properties that should be subject to future research efforts (see above). Overcoming these weaknesses would help to provide adequate model results that are suitable for addressing the future challenges to energy policy.

Apart from the need for further research, we also recommend policy makers to encourage the sharing of modeling expertise within a broader knowledge management strategy. In fact, for each policy research question analyzed in this chapter, we were able to find at least one model capable of adequately addressing the respective question. Yet, at the same time, other models with a high model-question gap exist and are likely to profit from a better dissemination of skills within the modeling community. We believe that an essential part of future research funding should be allocated for knowledge sharing via model documentation (tutorials, user guides, etc.), workshops, and online platforms. Networks such as the *Energy Modeling Forum*, the *Energy Modelling Platform for Europe*, or the *Research Network for Power System Analysis* in Germany can be used to coordinate future knowledge management to reduce the overall feature gap.

Appendix A

Appendix to Chapter 1

A.1 Nomenclature of numerical implementation

Table A.1: Nomenclature of model description

Symbol	Explanation
Sets	
$s \in \mathcal{S}$	Load segments
$t \in \mathcal{T}$	Time periods
$r \in \mathcal{R}$	Regions
$i \in \mathcal{I}$	Generation technologies
$j \in \mathcal{J}$	Storage technologies
$v \in \mathcal{V}$	Vintages
$f \in \mathcal{F}$	Fuel types
$n \in \mathcal{N}$	Natural gas supply classes
$b \in \mathcal{B}$	Biomass supply classes
Variables	
c^{tot}	Total system costs
$c^{\text{gc}}_{r,t}$	Investment costs for generation capacity
$c^{\text{tc}}_{r,t}$	Investment costs for transmission capacity
$c^{\text{sc}}_{r,t}$	Investment costs for storage capacity
$c^{\text{vc}}_{r,t}$	Operational costs for generation
$c^{\text{fom}}_{r,t}$	Maintenance costs for generation
$c^{\text{tvo}}_{r,t}$	Operation costs for transmission
$c^{\text{tfm}}_{r,t}$	Maintenance costs for transmission
tf_t	Investment tax factor
$gc^{\text{new}}_{i,r,t}$	New generation capacity
$tc^{\text{new}}_{r,rr,t}$	New transmission capacity
$sc^{\text{new}}_{j,r,t}$	New storage capacity
$mc_{i,r,t}$	Variable operational costs
$g_{s,i,v,r,t}$	Generation
$bs_{b,r,t}$	Biomass supply
$e_{s,r,rr,t}$	Electricity exchange
$gc_{i,v,r,t}$	Accumulated generation capacity
$tc_{r,rr,t}$	Accumulated transmission capacity
$sd_{s,j,r,t}$	Storage discharge
$s_{s,j,r,t}$	Storage charge
$tg_{i,v,r,t}$	Total generation
$cs_{r,t}$	Stored carbon
nbc_t	Amount of net banked carbon credits
cbc_t	Cumulative banked credits
Parameters	
TK	Investment tax rate
YR_t	Number of years since last time period
DF_t	Discount factor
$\text{IC}^{\text{gc}}_{i,t}$	Investment costs
$\text{LF}_{i,v,r,t}$	Life-time factor
$\text{IC}^{\text{tc}}_{r,rr}$	Investment costs for transmission capacity
$\text{IC}^{\text{sc}}_{j}$	Investment costs of storage
H_s	Number of represented hours
$\text{OC}^{\text{bio}}_{b,r}$	Operational costs for biomass supply
$\text{OC}^{\text{vom}}_{i,v,r}$	Operational costs
$\text{FC}_{i,f}$	Fuel costs
$\text{HR}_{i,v,f,r}$	Heat rate
$\text{FT}_{f,t}$	Time period-specific heat rate adjustment factor
$\text{FR}_{f,r}$	Region-specific heat rate adjustment factor
$\text{EM}_{i,v,r}$	Emission intensity
PC_t	Carbon permit price

Continued on next page

Table A.1 – *Continued from previous page*

Symbol	Explanation
$\mathrm{OC}^{\mathrm{fom}}_{i,r}$	Fixed operational costs
$\mathrm{OC}^{\mathrm{tvo}}_{r,rr}$	Operational costs for transmission
$\mathrm{OC}^{\mathrm{tfm}}_{r,rr,t}$	Maintenance costs for transmission
$\mathrm{PS}_{s,r}$	Self-consumption of hydro pump storage
$\mathrm{D}_{s,r,t}$	Demand
ϵ	Loss from storage discharge
δ	Loss from intra-regional distribution
$\mathrm{PEN}^{\mathrm{tr}}_{r,rr}$	Loss from transmission
$\mathrm{E}^{\mathrm{int}}_{s,r}$	Export to outside regions
$\mathrm{AF}_{s,i,r}$	Availability factor
$\mathrm{CF}_{s,i,r}$	Capacity factor
DF_{s}	Minimum dispatch factor for nuclear power plants
$\mathrm{CAP}^{\mathrm{gc}}_{i,r,t}$	Capacity limit
$\mathrm{CAP}^{\mathrm{geu}}_{i,t}$	Accumulated capacity limit
$\mathrm{L}_{i,v,r,t}$	Expected life-time
RF_{i}	Retrofit factor
CR_{i}	Conversion factor
$\mathrm{CAP}^{\mathrm{ret}}_{i,r}$	Capacity limit on CCS conversions
$\mathrm{GC}^{\mathrm{old}}_{i,v,r}$	Existing generation capacity
SH_{j}	Fixed storage size
$\mathrm{CAP}^{\mathrm{tc}}_{r,rr,t}$	Capacity limit on transmission capacity additions
$\mathrm{CAP}^{\mathrm{teu}}_{t}$	Capacity limit on accumulated transmission capacity additions
$\mathrm{TL}_{r,rr}$	Average transmission length
CR_{i}	Carbon capture rate
FC_{i}	Fuel coefficient
CC_{f}	Carbon content
$\mathrm{CAP}^{\mathrm{ccs}}_{r}$	Geologic storage limit
$\mathrm{QC}_{i,r}$	Share of initial capacity
$\mathrm{CAP}^{\mathrm{wind}}_{i,r}$	Wind power capacity limit
$\mathrm{CAP}^{\mathrm{solar}}_{i,r}$	Wind power capacity limit
$\mathrm{BS}_{b,r,t}$	Biomass supply
$\mathrm{GS}_{g,r,t}$	Gas supply
$\mathrm{CAP}^{\mathrm{co2}}_{t}$	Limit on accumulated carbon emissions

A.2 Model resolution

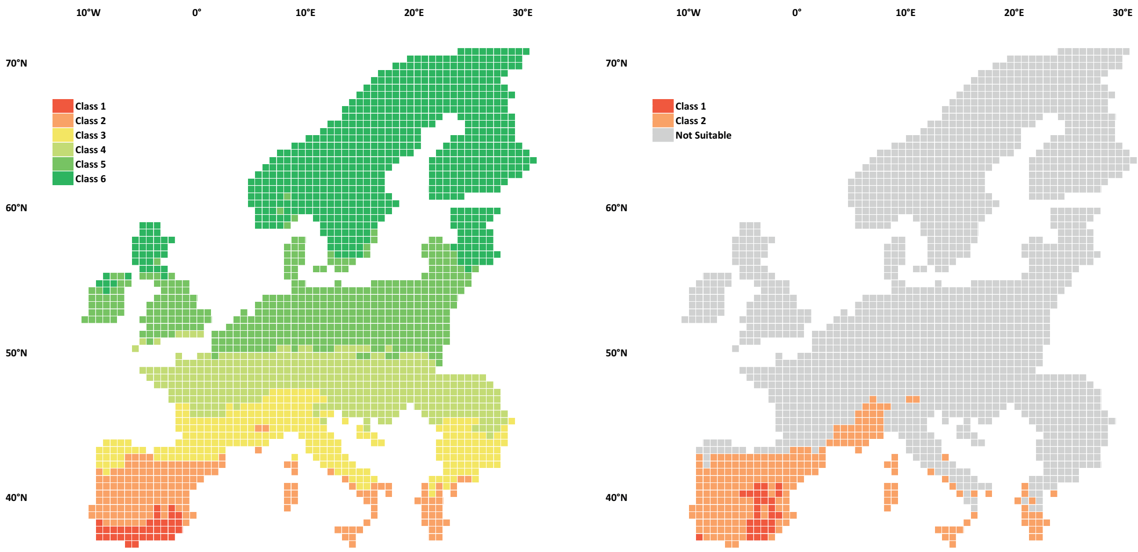
Table A.2: Composition of model regions

Region	Countries
Britain	United Kingdom, Ireland (UK, IE)
France	France (FR)
Benelux	Belgium, Luxembourg, Netherlands (BE, LU, NL)
Germany-N	Northern Germany (GER)
Germany-S	Southern Germany (GER)
Scandinavia	Denmark, Finland, Norway, Sweden (DK, FI, NO, SE)
Iberia	Portugal, Spain (PT, ES)
Alpine	Austria, Switzerland (AT, CH)
Italy	Italy (IT)
Eastern Europe-NW	Czech Republic, Poland, Slovak Republic (CZ, PL, SK)
Eastern Europe-NE	Estonia, Latvia, Lithuania (EE, LV, LT)
Eastern Europe-SW	Croatia, Hungary, Slovenia (HR, HU, SI)
Eastern Europe-SE	Bulgaria, Greece, Romania (BG, EL, RO)

Table A.3: Overview of types of generation technologies

Technology type	Technology name
lign	Lignite
lbcf	Lignite-biomass conversion
lgcs	Lignite with CCS
hdcl	Hard Coal
cbcl	Coal-biomass conversion
clcs	Coal with CCS
igcc	Coal with CC
ngcc	Natural gas combined-cycle
ngst	Natural gas stream turbine
nggt	Natural gas gas turbine
ngcs	Natural gas with CCS
ptsg	Petroleum steam/gas turbine
chp-g	Combined-heat-power with natural gas
chp-p	Combined-heat-power with petroleum
biow	Biomass Waste
bioe	Dedicated bioenergy
becs	Dedicated bioenergy with CCS
geot	Geothermal
nuc	Nuclear
hydro	Hydro
wind-on	Wind onshore
wind-os	Wind offshore
pv	stationary photovoltaic
pv-tk	Tracking photovoltaic
csp	Concentrated solar

A.3 Resource classes



(a) Distribution of solar resource classes **(b)** Distribution of CSP resource classes

Figure A.1: Solar resource data-base

A.4 Nomenclature of wind power representation

Table A.4: Nomenclature of wind power

Symbol	Explanation
Sets	
$s \in \mathcal{S}$	Time segments
$l \in \mathcal{L}$	Location
$h \in \mathcal{H}$	Hub height
$G \in \mathcal{G}$	Wind turbine types
$q \in \mathcal{Q}$	Site quality classes
$r \in \mathcal{R}$	Region
$c \in \mathcal{C}_{\text{wind}}$	Wind resource quality class
Parameters	
$s^{\text{v50}}_{s,l}$	Northward wind speed 50 meter above ground
$s^{\text{u50}}_{s,l}$	Eastward wind speed 50 meter above ground
HE_h	Hub height value
$\text{R}_{s,l}$	Surface roughness length
A_g	Constant from power curve interpolation
$\lambda^1_g - \lambda^6_g$	Coefficients from power curve interpolation
s^{up}_g	Upper wind speed limit
s^{low}_g	Lower wind speed limit
$W^{\text{wc}}_{l,r}$	Existing capacity distribution
$W^{\text{wt}}_{h,g,q,r}$	Existing technology-mix
$W^{\text{hub}}_{h,q,r}$	Assumed hub height mix
$W^{\text{q}}_{h,r}$	Assumed quality class mix
σ^u	General wind turbine loss factor
σ^p_s	Seasonal wind turbine loss factor
Variables	
$s^{50}_{s,l}$	Wind speed vector 50 meter above ground
$s_{s,l,h}$	Extrapolated wind speed
$wp^{\text{trb}}_{s,l,h,g}$	Normalized wind power output
$wp^{\text{hub}}_{s,h,q,r}$	Weighted normalized onshore wind power output
$wp^{on}_{s,r}$	Final existing onshore wind power output
$wp^{\text{hub-os}}_{s,h,r}$	Weighted normalized offshore wind power output
$wp^{os}_{s,r}$	Final existing offshore wind power output
$wp^{reg}_{s,r,c,h,g}$	Wind power output for quality classes
$wp_{s,r,c}$	Final new wind power output

A.5 Model for wind power output

In this appendix, we explain the translation of the two-dimensional wind speed vector to normalized wind power output. The estimation of wind power output uses wind speed, displacement height, and surface roughness as input parameters. We combine the wind speed at each location l and time segment s from two directions ($s^{\mathrm{v50}}_{s,l}$ and $s^{\mathrm{u50}}_{s,l}$) to a single one $s^{50}_{s,l}$ by Equation (A.1):

$$s^{50}_{s,l} = \sqrt{s^{\mathrm{v50}}_{s,l} + s^{\mathrm{u50}}_{s,l}} \qquad \forall s \in \mathcal{S}, l \in \mathcal{L} \tag{A.1}$$

In the following, we use a portfolio-approach for a better approximation of observed generation profiles. Based on the Monin-Obukhov specification, we extrapolate wind speeds at each location to different hub heights h, with the value of each hub height HE_h and the surface roughness length $\mathrm{R}_{s,l}$, as depicted in Equation (A.2):

$$s_{s,l,h} = s^{50}_{s,l} \cdot \left(\frac{log(\frac{\mathrm{HE}_h}{\mathrm{R}_{s,l}})}{log(\frac{50}{\mathrm{R}_{s,l}})} \right) \qquad \forall s \in \mathcal{S}, l \in \mathcal{L}, h \in \mathcal{H} \tag{A.2}$$

Then, wind speeds at hub heights are translated to normalized wind power output $wp^{\mathrm{trb}}_{s,l,h,g}$ for different wind turbines g by means of their respective power curves, which are shown in Figure A.2. The relationship between wind speed and power curve-specific output can be approximated by the function shown in Equation (A.3), which is an interpolation of the piecewise-defined power curve. The value of the parameters A_g, λ^1_g,...,λ^6_g are derived from this interpolation:

$$\begin{aligned} wp^{\mathrm{trb}}_{s,l,h,g} &= \mathrm{A}_g + \lambda^1_g \cdot s_{s,l,h} + (\lambda^2_g \cdot s_{s,l,h})^2 + (\lambda^3_g \cdot s_{s,l,h})^3 + (\lambda^4_g \cdot s_{s,l,h})^4 \\ &+ (\lambda^5_g \cdot s_{s,l,h})^5 + (\lambda^6_g \cdot s_{s,l,h})^6 \qquad \forall s \in \mathcal{S}, l \in \mathcal{L}, h \in \mathcal{H}, g \in \mathcal{G} \end{aligned} \tag{A.3}$$

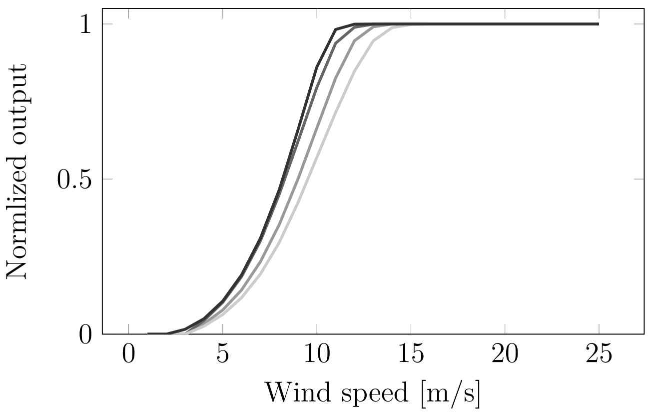


Figure A.2: Turbine power curves

A.6 Nomenclature of solar power representation

Table A.5: Nomenclature of solar power

Symbol	Explanation
Sets	
$s \in \mathcal{S}$	Time segments
$l \in \mathcal{L}$	Location
$r \in \mathcal{R}$	Region
$o \in \mathcal{O}$	Panel orientations
$p \in \mathcal{P}$	Panel tilts
$c \in \mathcal{C}_{\text{solar}}$	Solar resource quality class
Parameters	
E^{sc}	Solar constant
V_s	Day number of the year
LON_l	Longitude
LAT_l	Latitude
$LST_{s,l}$	Local solar time
$GHI_{s,l}$	Global horizontal irradiation
α_o^2	Panel orientation value
$\beta_{l,p}^2$	Panel tilt value
ρ	Reflection coefficient
T^r	Rated module temperature
$T_{s,l}$	Ambient temperature
η^r	Rated module efficiency
P^r	Rated power output
$W_{l,r}^{\text{sc}}$	Existing capacity distribution
$W_{o,p}^{\text{st}}$	Assumed orientation and panel tilt mix
$C_{r,l,c}^{\text{solar}}$	Resource class allocation
Variables	
$e_{s,l}^0$	Apparent extraterrestrial solar irradiation
$\beta_{s,l}^1$	Altitude angle
δ_s	Declination angle
$\omega_{s,l}$	Hour angle
$AST_{s,l}$	Apparent solar time
$LSTM_l$	Local longitude of standard time meridian
EOT_s	Equation of time
DV_s	Daily correction value
$k_{s,l}$	Clearness index
$d_{s,l}$	Share of diffuse irradiation
$dif_{s,l}$	Diffuse irradiation
$dni_{s,l}$	Direct normal irradiation
$\alpha_{s,l}^1$	Azimuth angle
$\theta_{s,l}$	Collector angle
$r_{s,l,o,p}^{tot}$	Solar irradiation at module
$r_{s,l,o,p}^{d}$	Direct component of solar irradiation at module
$r_{s,l,p}^{dif}$	Diffuse-scattered component of solar irradiation at module
$r_{s,l,p}^{ref}$	Reflected component of solar irradiation at module
$t_{s,l,o,p}^{pv}$	Actual module temperature
$\eta_{s,l,o,p}$	Panel efficiency
$sp_{s,l,o,p}^{pv}$	Actual module output
$\eta_{s,l,o,p}^{inv}$	Inverter efficiency
$sp_{s,l,o,p}$	Normalized solar power output by location
$sp_{s,r,o,p}^{reg}$	Normalized solar power output by region
$sp_{s,r}^{pv}$	Final existing pv power output
$sp_{s,i,r}^{pv}$	Final new pv power output

A.7 Separation of solar irradiation

In this appendix, we describe how the solar irradiation data from NASA (2010) can be separated into its direct and diffuse component. Modeling the output from solar power technologies requires, among others, a time-series on the direct and diffuse irradiance. Most publicly available data, including MERRA, provides only GHI as a variable. Therefore, GHI has to be separated into the direct and diffuse part. For that purpose, as done in Juruš et al. (2013), we adopt the Boland-Ridley-Lauret model (Ridley et al., 2010), that estimates the share of diffuse irradiation from the clearness index. The methodology is based on the following main steps:

First, the seasonal variation of the apparent extraterrestrial solar irradiation[1] has to be estimated according to Equation (A.4) (Lunde, 1980):

$$e^0_{s,l} = E^{sc} \cdot \left(1 + 0.033 \cdot cos(\frac{V_s}{|S|} \cdot 360ř)\right) \cdot cos(\beta^1_{s,l}) \qquad \forall s \in \mathcal{S}, l \in \mathcal{L} \tag{A.4}$$

with the solar constant $E^{sc} = 1,367$[2], the number of time segment V_s, the total number of time segments $|S|$, and the altitude angle $\beta^1_{s,l}$.[3] The calculation of $\beta^1_{s,l}$ is based on Equations (A.5)–(A.11) and are explained in more detail in Masters (2004):

$$\beta^1_{s,l} = \sin^{-1}\left(\sin(\delta_s) \cdot \sin(LON_l) + \cos(\delta_h) \cdot \cos(LAT_l) \cdot \cos(\omega_{s,l})\right) \qquad \forall s \in \mathcal{S}, l \in \mathcal{L} \tag{A.5}$$

With longitude LON_l, latitude LAT_l, and declination angle δ_s for the northern hemisphere being defined as:

$$\delta_s = 23.45° \cdot \sin\left(\frac{V_s + 6816}{|S|} \cdot 360°\right) \qquad \forall s \in \mathcal{S} \tag{A.6}$$

an hour angle $\omega_{s,l}$ comprising:

$$\omega_{s,l} = 15° \cdot (AST_{s,l} - 12) \qquad \forall s \in \mathcal{S}, l \in \mathcal{L}. \tag{A.7}$$

Furthermore, the following equations have to be considered to approximate the apparent solar time $AST_{s,l}$ by the local solar time $LST_{s,l}$, local longitude of standard time meridian

---

[1] Seasonal variations result from the varying distance between the earth and the sun.

[2] The solar constant E^{sc} is the solar irradiation at a plane normal to the sun at the top of the atmosphere.

[3] The altitude angle $\beta^1_{s,l}$ is the vertical angle between the sun's rays and the horizon.

$LSTM_l$, longitude LON_l, and equation of time EOT_s.

$$AST_{s,l} = LST_{s,l} + 4 \cdot (LSTM_l - LON_l) + EOT_s \qquad \forall s \in \mathcal{S}, l \in \mathcal{L} \tag{A.8}$$

$$LSTM_l = 15^\circ \cdot \frac{LON_l}{15^\circ} \qquad \forall l \in \mathcal{L} \tag{A.9}$$

$$EOT_s = 9.87 \cdot \sin(2 \cdot DV_s) - 7.53 \cdot \cos(DV_s) - 1.5 \cdot \sin(DV_s) \qquad \forall s \in \mathcal{S} \tag{A.10}$$

$$DV_s = 360^\circ \cdot \frac{V_s + 1944}{|S|} \qquad \forall s \in \mathcal{S} \tag{A.11}$$

Then, based on $e^0_{s,l}$, we can calculate the clearness index $k_{s,l}$[4] as the share of global horizontal irradiation $GHI_{s,l}$ in $e^0_{s,l}$ (Equation (A.12)) (Boilley and Wald, 2015):

$$k_{s,l} = \frac{GHI_{s,l}}{e^0_{s,l}} \qquad \forall s \in \mathcal{S}, l \in \mathcal{L} \tag{A.12}$$

which is then used in Equation (A.12) to estimate the share of diffuse irradiation $d_{s,l}$ in $GHI_{s,l}$ (Ridley et al., 2010):

$$d_{s,l} = \frac{1}{1 + e^{-5.0033 + 8.605 \cdot k_{s,l}}} \qquad \forall s \in \mathcal{S}, l \in \mathcal{L} \tag{A.13}$$

In a last step, we calculate diffuse irradiation (DIF) $dif_{s,l}$ (Equation (A.14)) and direct normal irradiation (DNI) $dni_{s,l}$ (Equation (A.15)). With $dif_{s,l}$ as the product of $GHI_{s,l}$ and $d_{s,l}$:

$$dif_{s,l} = d_{s,l} \cdot GHI_{s,l} \qquad \forall s \in \mathcal{S}, l \in \mathcal{L} \tag{A.14}$$

and $dni_{s,l}$ being additionally adjusted for the altitude angle:[5]

$$dni_{s,l} = \frac{(1 - d_{s,l}) \cdot GHI_{s,l}}{\sin(\beta^1_{s,l})} \qquad \forall s \in \mathcal{S}, l \in \mathcal{L} \tag{A.15}$$

[4] The clearness index $k_{s,l}$ is a measures for the clearness of the atmosphere. A value of 0.7 indicates a clear sky (Boilley and Wald, 2015).

[5] GHI measures only the horizontal, i.e., perpendicular to the earth's surface, irradiation. To additionally account for the non-horizontal irradiation in DNI, we adjust for the altitude angle.

A.8 Model for photovoltaic power output

In this appendix, we depict the translation of solar irradiation into normalized solar power output. With the separation of GHI into the DIF and DNI component in Appendix A.7, irradiation data can be converted into generation profiles for PV, PV-TK, and CSP technologies (Masters, 2004). We start off by calculating the azimuth angle $\alpha^1_{s,l}$ according to Equation (A.16):[6]

$$\alpha^1_{s,l} = \cos^{-1}\left(\frac{\sin(\delta_s)\cdot\cos(LAT_l) - \cos(\delta_s)\cdot\sin(LAT_l)\cdot\cos(\omega_{s,l})}{\cos(\beta^1_{s,l})}\right) \qquad \forall s \in \mathcal{S}, l \in \mathcal{L} \tag{A.16}$$

This feeds into the calculation of the collector angle $\theta_{s,l}$ in (Equation (A.17)).[7] In analogy to wind power, we apply a portfolio approach and calculate output values for different panel orientations o with the parameter α^2_o and tilts p represented by $\beta^2_{l,p}$:[8]

$$\theta_{s,l,o,p} = \cos(\beta^1_{s,l})\cdot\sin(\beta^2_{l,p})\cdot\cos(\alpha^1_{s,l} - \alpha^2_l) + \sin(\beta^1_{s,l})\cdot\cos(\beta^2_{l,p}) \qquad \forall s \in \mathcal{S}, l \in \mathcal{L}, o \in \mathcal{O}, p \in \mathcal{P} \tag{A.17}$$

This allows for calculating the solar irradiation at the module $r^{tot}_{s,l,o,p}$ (Equation (A.18)), that is composed of the direct component $r^d_{s,l,o,p}$, diffuse-scattered component $r^{dif}_{s,l,p}$, and reflected component $r^{ref}_{s,l,p}$.

$$r^{tot}_{s,l,o,p} = r^d_{s,l,o,p} + r^{dif}_{s,l,p} + r^{ref}_{s,l,p} \qquad \forall s \in \mathcal{S}, l \in \mathcal{L}, o \in \mathcal{O}, p \in \mathcal{P} \tag{A.18}$$

$$r^d_{s,l,o,p} = dni_{s,l}\cdot\theta_{s,l,o,p} \qquad \forall s \in \mathcal{S}, l \in \mathcal{L}, o \in \mathcal{O}, p \in \mathcal{P} \tag{A.19}$$

$$r^{dif}_{s,l,p} = dif_{s,l}\cdot\frac{1 + cos(\beta^2_{l,p})}{2} \qquad \forall s \in \mathcal{S}, l \in \mathcal{L}, p \in \mathcal{P} \tag{A.20}$$

$$r^{ref}_{s,l,p} = dni_{s,l}\cdot\rho\cdot\left(\frac{dif_{s,l}}{dni_{s,l}} + \sin(\beta^1_{s,l})\right)\cdot\frac{1 - cos(\beta^2_{l,p})}{2} \qquad \forall s \in \mathcal{S}, l \in \mathcal{L}, p \in \mathcal{P} \tag{A.21}$$

The reflection coefficient ρ has a default value of 0.2 for an ordinary ground (Masters, 2004), which is understood as area not covered with snow and, hence, has a lower reflection.

To get the actual feed-in profile, the solar irradiation at the module has to be adjusted for the panel efficiency, at first, and the inverter efficiency, in a second step. The panel

---

[6] The azimuth angle $\alpha^1_{s,l}$ is the horizontal angle of the sun's rays relative to geographic north.

[7] The collector angle $\theta_{s,l}$ is the horizontal angle of the sun's rays to the panel.

[8] The panel orientation α^2_o indicates the facing relative to the north with $\alpha^2_o = 180°$ implying a south-facing panel.

efficiency is a function of the module's rated temperature T^r and the actual module temperature $t^{pv}_{s,l,o,p}$, which can be estimated from the ambient temperature $T_{s,l}$ and the irradiation at the module as shown in Equations (A.22) and (A.23). The rated temperature, which is understood as the temperature at which the nominal power output is reached, is set to $T^r = 25°$ (Kalogirou, 2009). Higher module temperatures lead to a reduction in its output:

$$\eta_{s,l,o,p} = 1 - \gamma \cdot (t^{pv}_{s,l,o,p} - T^r) \qquad \forall s \in \mathcal{S}, l \in \mathcal{L}, o \in \mathcal{O}, p \in \mathcal{P} \tag{A.22}$$

$$t^{pv}_{s,l,o,p} = 30+0.0175\cdot(r^{tot}_{s,l,o,p}-300)+1.14\cdot(T_{s,l}-25) \qquad \forall s \in \mathcal{S}, l \in \mathcal{L}, o \in \mathcal{O}, p \in \mathcal{P} \tag{A.23}$$

Then, we can calculate the actual module output $sp^{pv}_{s,l,o,p}$ (Equation (A.24)) by combining $\eta_{s,l,o,p}$, the rated module efficiency η^r, and the irradiation at the module $r^{tot}_{s,l,o,p}$

$$sp^{pv}_{s,l,o,p} = \eta_{s,l,o,p} \cdot \eta^r \cdot r^{tot}_{s,l,o,p} \qquad \forall s \in \mathcal{S}, l \in \mathcal{L}, o \in \mathcal{O}, p \in \mathcal{P} \tag{A.24}$$

and estimate the inverter efficiency $\eta^{inv}_{s,l,o,p}$. The efficiency of the conversion from direct current (DC) to alternating current (AC) is dynamic and increases concave downward with the module output $sp^{pv}_{s,l,o,p}$. Due to a lack of functional formulation of the inverter efficiency, we estimate it with the function shown in Equation (A.25):

$$\eta^{inv}_{s,l,o,p} = \left(\frac{0.5}{sp^{pv}_{s,l,o,p}}\right)^{\frac{1}{10}} \qquad \forall s \in \mathcal{S}, l \in \mathcal{L}, o \in \mathcal{O}, p \in \mathcal{P} \tag{A.25}$$

Finally, we can estimate the normalized solar power output $sp_{s,l,o,p}$ (normalized to the rated power output P^r) in Equation (A.26):

$$sp_{s,l,o,p} = \frac{\eta^{inv}_{s,l,o,p} \cdot sp^{pv}_{s,l,o,p}}{P^r} \qquad \forall s \in \mathcal{S}, l \in \mathcal{L}, o \in \mathcal{O}, p \in \mathcal{P} \tag{A.26}$$

A.9 Nomenclature of concentrated solar power representation

Table A.6: Nomenclature of CSP

Symbol	Explanation
Sets	
$s \in \mathcal{S}$	Time segments
$r \in \mathcal{R}$	Region
$i \in \mathcal{I}$	Generation technologies
Parameters	
$P_{s,r}$	Exogenous market prices
$dni_{s,i,r}$	Incoming direct solar irradiation
SM	Solar multiple
SH^{csp}	Storage capacity
ϵ^{csp}	Loss factor
Variables	
rev	Revenue
$g_{s,i,r}$	CSP disptach
$s^{csp}_{s,i,r}$	CSP storage charge
$sd^{csp}_{s,i,r}$	CSP storage discharge
$sb^{csp}_{s,i,r}$	Accumulated CSP storage

A.10 Input data

Table A.7: Overview of lifetime, fixed, and variable O&M costs

Technology	Life-time [Years]	Fixed O&M costs [€/kW]	Variable O&M costs [€/MWh]
lign	60	30	7
lbcf	60	-	-
lgcs	60	-	-
hdcl	30	6	-
cbcl	60	-	-
clcs	60	100	13
igcc	60	60	6
ngcc	40	20	4
ngst	60	20	4
nggt	40	15	3
ngcs	40	30	12
ptsg	60	20	3
chp-g	100	-	-
chp-p	100	-	-
biow	100	30	20
bioe	40	80	7
becs	40	120	14
geot	80	80	9
nuc	60	100	10
hydro	100	-	-
wind-on	30	35	0
wind-os	20	80	0
pv	20	25	0
pv-tk	20	30	0
csp	30	30	0

Table A.8: Overview of investment costs [€/kW]

	2020	2025	2030	2035	2040	2045	2050
hdcl	1,300	1,300	1,300	1,300	1,300	1,300	1,300
clcs	2,924	2,888	2,852	2,818	2,784	2,752	2,720
igcc	1,800	1,800	1,800	1,800	1,800	1,800	1,800
ngcc	800	800	800	800	800	800	800
nggt	400	400	400	400	400	400	400
ngcs	1,367	1,352	1,337	1,322	1,308	1,294	1,280
bioe	2,350	2,278	2,209	2,141	2,076	2,013	1,951
becs	4,000	3,800	3,600	3,400	3,300	3,200	3,100
geot	3,775	3,578	3,392	3,216	3,049	2,890	2,740
nuc	5,000	5,000	5,000	5,000	5,000	5,000	5,000
wind-on	1,240	1,210	1,182	1,154	1,127	1,101	1,075
wind-os	2,742	2,621	2,506	2,396	2,290	2,189	2,093
pv	1,100	1,000	950	900	850	800	750
pv-tk	1,375	1,260	1,188	1,125	1,063	1,000	938
csp	4,500	4,050	3,645	3,463	3,290	3,125	2,969

Table A.9: Overview of final electricity demand projection [TWh]

Region	2015	2050	Growth rate
Austria	60	84	40%
Belgium	87	121	39%
Bulgaria	28	34	21%
*Croati*a	20	24	19%
Czech Republic	64	71	11%
Denmark	35	43	23%
Estonia	7	12	71%
Finland	89	84	-6%
France	459	657	43%
Germany	553	661	20%
Greece	60	67	12%
Hungary	36	60	67%
Ireland	28	42	50%
Italy	324	527	63%
Latvia	7	27	286%
Lithuania	9	37	311%
Luxembourg	8	8	0%
Netherlands	114	170	49%
Norway	150	112	-25%
Poland	126	160	27%
Portugal	49	75	53%
Romania	46	64	39%
Slovakia	29	28	-3%
Slovenia	14	14	0%
Spain	275	529	92%
Sweden	136	127	-7%
Switzerland	55	97	78%
United Kingdom	356	389	9%

Table A.10: Overview of existing transfer capacities between regions [GW]

	Britain	*France*	*Benelux*	*Ger-N*	*Ger-S*	*Scanda*	*Iberia*	*Alpine*	*Italy*	*EE-NW*	*EE-NE*	*EE-SW*	*EE-SE*
Britain	-	2	1	-	-	-	-	-	-	-	-	-	-
France	2	-	3.4	-	2.7	-	1.3	3.2	2.58	-	-	-	-
Benelux	1	2.3	-	3	-	0.7	-	-	-	-	-	-	-
Ger-N	-	-	3.85	-	16	2.15	-	-	-	1.2	-	-	-
Ger-S	-	-	0.98	16	-	-	-	3.7	-	0.8	-	-	-
Scanda	-	-	0.7	2.70	-	-	-	-	-	0.6	0.35	-	-
Iberia	-	0.5	-	-	-	-	-	-	-	-	-	-	-
Alpine	-	1.1	-	-	5.5	-	-	-	4.39	0.6	-	1.7	-
Italy	-	1	-	-	-	-	-	2.1	-	-	-	0.16	0.5
EE-NW	-	-	-	1.1	2.3	-	-	1	-	-	-	1.3	-
EE-NE	-	-	-	-	-	0.35	-	-	-	-	-	-	-
EE-SW	-	-	-	-	-	-	-	1.7	0.58	0.6	-	-	0.7
EE-SE	-	-	-	-	-	-	-	-	0.5	-	-	0.7	-

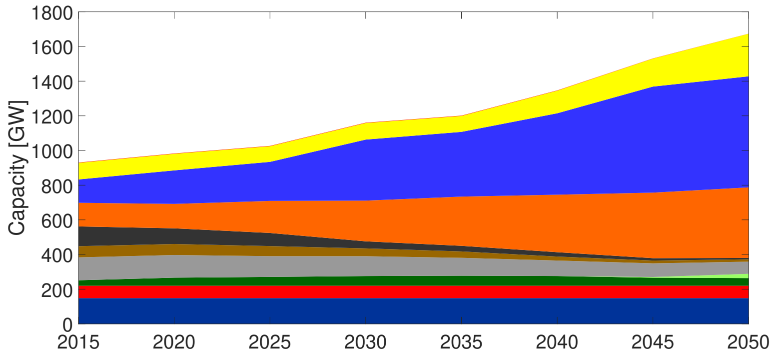
Table A.11: Overview of limits for investment in transfer capacities in 2030 [GW]

	Britain	*France*	*Benelux*	*Ger-N*	*Ger-S*	*Scanda*	*Iberia*	*Alpine*	*Italy*	*EE-NW*	*EE-NE*	*EE-SW*	*EE-SE*
Britain	-	-	0.16	-	-	0.7	-	-	-	-	-	-	-
France	-	-	-	-	-	-	0.7	-	-	-	-	-	-
Benelux	0.16	-	-	-	-	0.15	-	-	-	-	-	-	-
Ger-N	-	-	-	-	1	0.68	-	-	-	0.35	-	-	-
Ger-S	-	-	-	1	-	-	-	0.49	-	0.35	-	-	-
Scanda	0.7	-	0.45	0.39	-	-	-	-	-	-	1	-	-
Iberia	-	1.5	-	-	-	-	-	-	-	-	-	-	-
Alpine	-	0.5	-	-	-	-	-	-	-	0.7	-	-	-
Italy	-	0.3	-	-	-	-	-	0.86	-	-	-	1.42	-
EE-NW	-	-	-	0.4	-	-	-	0.75	-	-	0.5	0.2	-
EE-NE	-	-	-	-	-	1	-	-	-	0.5	-	-	-
EE-SW	-	-	-	-	-	-	-	-	0.99	0.45	-	-	-
EE-SE	-	-	-	-	-	-	-	-	-	-	-	-	-

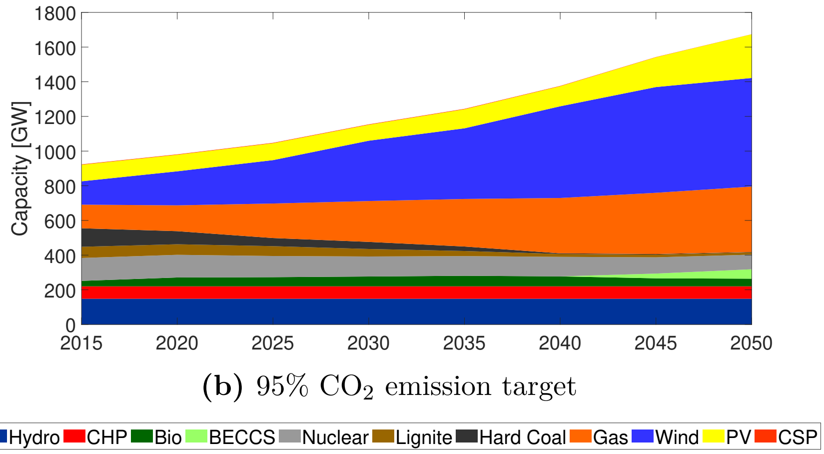
Table A.12: Overview of limits for investment in transfer capacities in 2050 [GW]

	Britain	*France*	*Benelux*	*Ger-N*	*Ger-S*	*Scanda*	*Iberia*	*Alpine*	*Italy*	*EE-NW*	*EE-NE*	*EE-SW*	*EE-SE*
Britain	-	0.67	0.44	-	-	0.47	-	-	-	-	-	-	-
France	0.67	-	0.2	-	0.1	-	0.9	-	0.54	-	-	-	-
Benelux	0.44	0.27	-	0.83	-	0.33	-	-	-	-	-	-	-
Ger-N	-	-	0.83	-	1	1.17	-	-	-	0.63	-	-	-
Ger-S	-	-	-	1	-	-	-	1.56	-	0.5	-	-	-
Scanda	0.47	-	0.53	1.16	-	-	-	-	-	-	0.78	-	-
Iberia	-	1.17	-	-	-	-	-	-	-	-	-	-	-
Alpine	-	0.4	-	-	1.63	-	-	-	1.45	0.67	-	0.33	-
Italy	-	0.53	-	-	-	-	-	1.27	-	-	-	1	0.17
EE-NW	-	-	-	0.63	0.5	-	-	0.83	-	-	0.33	0.57	-
EE-NE	-	-	-	-	-	0.78	-	-	-	0.33	-	-	-
EE-SW	-	-	-	-	-	-	-	0.23	0.86	0.5	-	-	-
EE-SE	-	-	-	-	-	-	-	-	0.17	-	-	-	-

A.11 Capacity investment paths



(a) 80% CO_2 emission target



(b) 95% CO_2 emission target

Figure A.3: Long-run capacity path with 80% and 95% CO_2 emission reduction target

Appendix B

Appendix to Chapter 2

B.1 Implementation of the nucleolus

The nucleolus can be found by a sequence of linear programs. The first program of this sequence tries to find the optimal pre-imputation x_i^{NUC}, which maximizes the excess ε across all coalitions S. Conditions (B.2) and (B.3) ensure that ε equals the minimum excess and that the efficiency condition is met.

$$\max_{x_i^{NUC}} \quad \varepsilon \tag{B.1}$$

subject to:

$$\varepsilon + \sum_{i \in S} x_i^{NUC} \leq \sum_{i \in S} \hat{x}_i(S) \quad \forall S \subset N,\ S \neq \emptyset \tag{B.2}$$

$$\sum_{i \in N} x_i^{NUC} = \sum_{i \in N} \hat{x}_i(N) \tag{B.3}$$

$$x_i^{NUC} \geq 0 \tag{B.4}$$

Yet, the solution to this problem is not necessarily unique. As shown in Fromen (1997), only the sequence of $k = 2^n - 2$ linear programs finds the unique solution to the gain-sharing problem. The program above represents the first program with $k = 1$ in this sequence. The subsequent programs ($k > 1$) are formulated by means of the following conditions:

$$\max_{x_i^{NUC}} \quad \varepsilon_k \tag{B.5}$$

subject to:

$$\varepsilon_k + \sum_{i \in S} x_i^{NUC} \leq \sum_{i \in S} \hat{x}_i(S) \quad \forall S \subset N,\ S \notin F_k \tag{B.6}$$

$$\varepsilon_l + \sum_{i \in S} x_i^{NUC} = \sum_{i \in S} \hat{x}_i(S) \quad \forall S \in F_l,\ l \in \{1, ..., k-1\} \tag{B.7}$$

$$\sum_{i \in N} x_i^{NUC} = \sum_{i \in N} \hat{x}_i(N) \tag{B.8}$$

$$x_i^{NUC} \geq 0 \tag{B.9}$$

As in the case of $k = 1$, Constraints (B.6) and (B.9) secure that ε_k is minimized and the program's efficiency holds. Condition (B.7) additionally ensures that the excess of all coalitions, comprised in the set F_l, must equal the excess of the l^{th} program. The set F_l is determined for each program k and contains all coalitions fulfilling the condition $\sum_{i \in S} x_i^{NUC} + \varepsilon_{k-1} = \sum_{i \in S} \hat{x}_i(S)$. Furthermore, set F_k is determined iteratively by $F_k = \cup_{l<k} F_l$.

If the (N, v) game exhibits an empty core, the linear program additionally requires the individual rationality constraint (Guajardo and Jörnsten, 2015):

$$x_i^{NUC} \leq c_i(\{i\}). \tag{B.10}$$

B.2 Cost-sharing game results

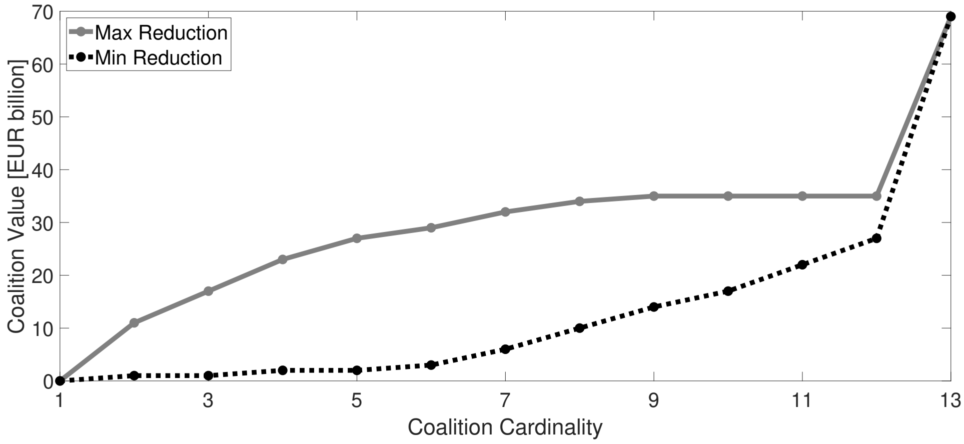
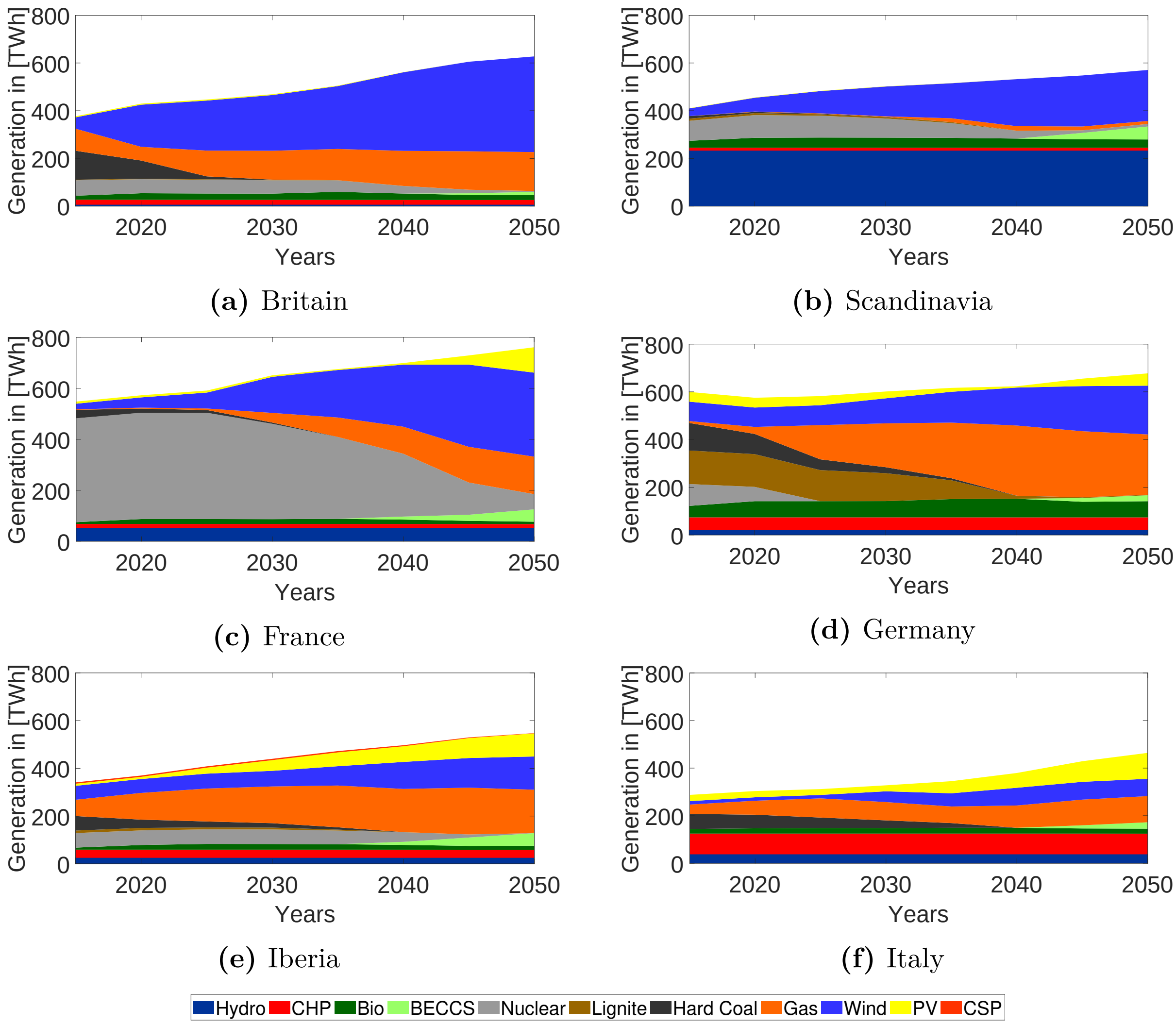


Figure B.1: Coalition value by coalition cardinality

B.3 Market outcomes



(a) Britain

(b) Scandinavia

(c) France

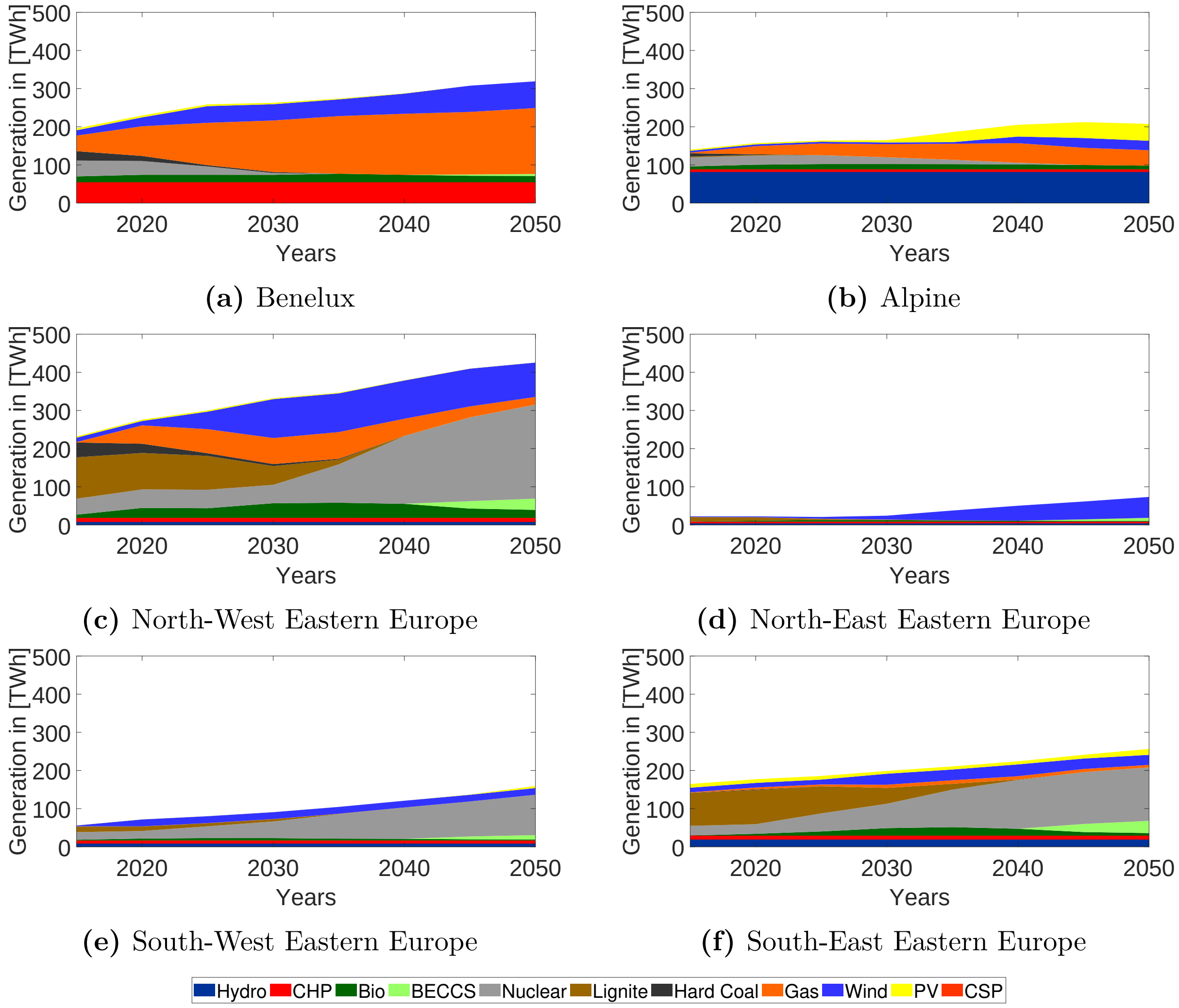
(d) Germany

(e) Iberia

(f) Italy

Figure B.2: Long-run regional generation paths under grand coalition (part I)

Note: The generation path in Figure B.2d comprises both German model regions.



(a) Benelux

(b) Alpine

(c) North-West Eastern Europe

(d) North-East Eastern Europe

(e) South-West Eastern Europe

(f) South-East Eastern Europe

Figure B.3: Long-run regional generation paths under grand coalition (part II)

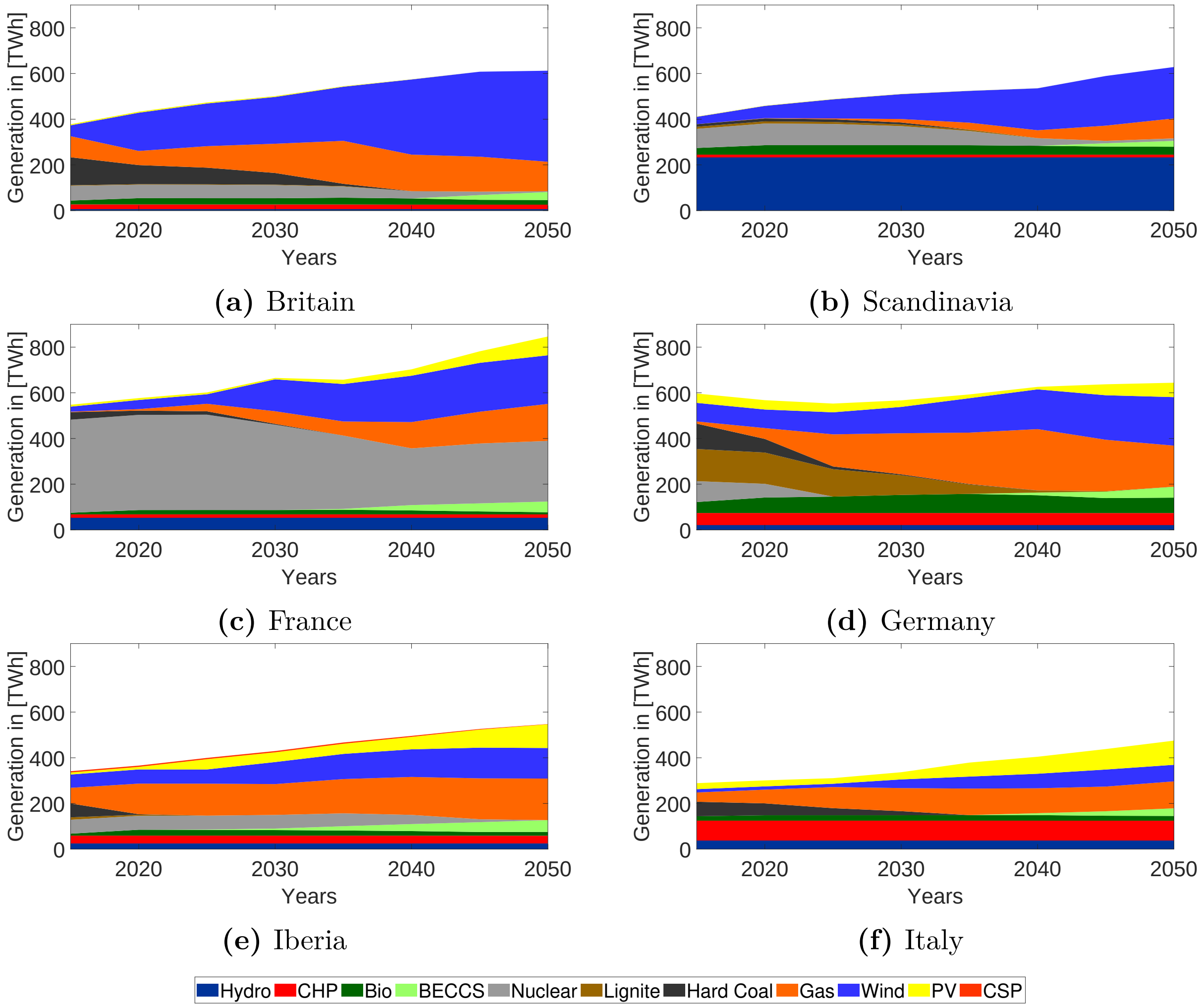
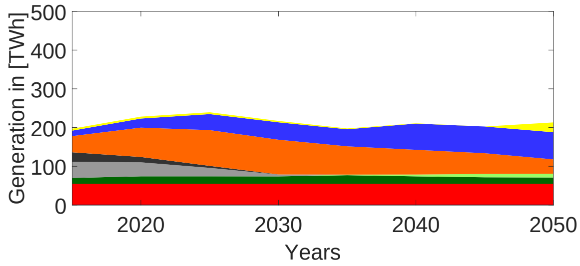
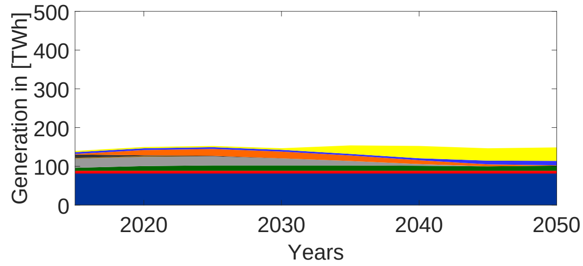


Figure B.4: Long-run regional generation paths under singleton coalitions (part I)

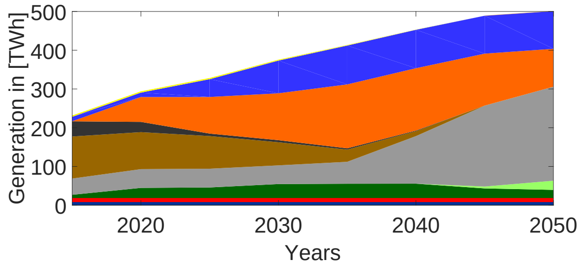
Note: The generation path in Figure B.4d comprises both German model regions.



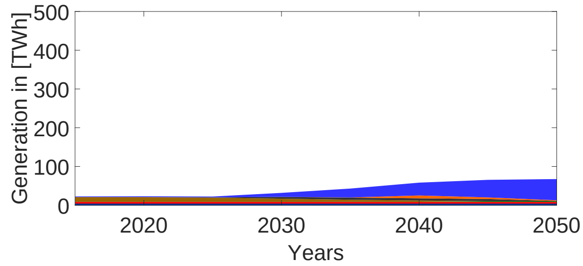
(a) Benelux



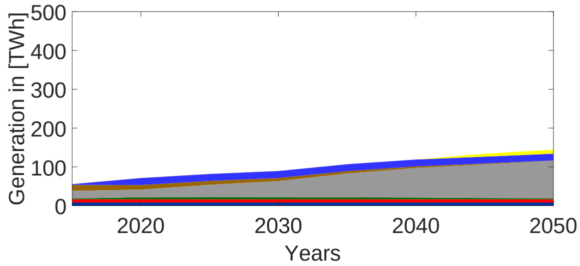
(b) Alpine



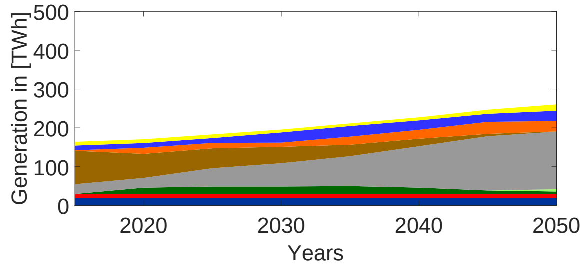
(c) North-West Eastern Europe



(d) North-East Eastern Europe



(e) South-West Eastern Europe



(f) South-East Eastern Europe

Figure B.5: Long-run regional generation paths under singleton coalitions (part II)

Table B.1: Regional relative energy-only prices under grand coalition (compared to 2015)

	2020	2025	2030	2035	2040	2045	2050
Britain	0.90	0.99	0.98	1.01	1.08	1.12	1.13
France	1.03	1.18	1.15	1.21	1.29	1.33	1.35
Benelux	1.04	1.11	1.14	1.19	1.31	1.36	1.40
Germany-N	1.11	1.20	1.22	1.26	1.35	1.39	1.41
Germany-S	1.13	1.21	1.23	1.29	1.42	1.47	1.47
Scandinavia	1.06	1.10	1.10	1.19	1.30	1.36	1.36
Iberia	1.06	1.11	1.13	1.15	1.22	1.26	1.26
Alpine	1.08	1.14	1.17	1.21	1.31	1.33	1.32
Italy	1.05	1.12	1.12	1.14	1.21	1.24	1.27
Eastern Europe-NW	1.03	1.07	1.07	1.11	1.12	1.12	1.13
Eastern Europe-NE	1.07	1.07	1.02	0.98	1.07	1.09	1.08
Eastern Europe-SW	1.01	1.06	1.08	1.09	1.13	1.15	1.16
Eastern Europe-SE	1.32	1.37	1.38	1.40	1.42	1.43	1.44

Table B.2: Regional relative energy-only prices under singleton coalitions (compared to 2015)

	2020	2025	2030	2035	2040	2045	2050
Britain	0.87	0.88	0.86	0.89	1.01	1.06	1.07
France	1.00	1.11	1.06	1.20	1.23	1.25	1.25
Benelux	0.98	1.05	1.11	1.23	1.27	1.35	1.37
Germany-N	1.04	1.15	1.18	1.25	1.31	1.35	1.37
Germany-S	1.06	1.17	1.21	1.29	1.36	1.38	1.39
Scandinavia	1.01	1.03	0.99	1.10	1.20	1.25	1.28
Iberia	1.20	1.27	1.17	1.18	1.18	1.18	1.17
Alpine	1.03	1.09	1.11	1.15	1.20	1.22	1.22
Italy	1.05	1.11	1.11	1.13	1.16	1.18	1.19
Eastern Europe-NW	0.99	1.03	1.00	1.04	1.07	1.10	1.12
Eastern Europe-NE	0.96	0.97	0.94	0.97	1.05	1.08	1.06
Eastern Europe-SW	1.00	1.03	1.04	1.06	1.10	1.12	1.11
Eastern Europe-SE	1.47	1.35	1.37	1.38	1.39	1.40	1.42

Appendix C

Appendix to Chapter 3

C.1 Electricity demand assumptions

Table C.1: Existing energy efficiency level and energy service demand projection

	EE indicator				2015 EE capacity [GW]				Demand [TWh]		
	Ind	Res	Com	Tra	Ind	Res	Com	Tra	1990	2015	2050
AT	0.16	0.32	0.30	0.09	0.32	0.42	0.34	0.03	42	60	84
BE	0.35	0.30	0.06	0.16	1.18	0.45	0.08	0.02	57	87	121
BG	0.56	0.21	0.19	0.12	1.31	0.25	0.11	0.02	37	28	34
CH	0.15	0.25	0.29	0.15	0.18	0.47	0.47	0.04	44	55	97
CZ	0.37	0.21	0.20	0.02	1.12	0.23	0.15	0.01	46	64	71
DE	0.13	0.31	0.16	0.17	3.02	4.12	2.03	0.27	453	553	661
DK	0.25	0.23	0.08	0.12	0.24	0.26	0.10	0.00	28	35	43
EE	0.52	0.23	0.09	0.16	0.16	0.02	0.02	0.01	6	7	12
EL	0.29	0.28	0.07	0.41	0.41	0.29	0.06	0.01	28	60	67
ES	0.22	0.26	0.28	0.14	1.60	0.89	0.92	0.06	126	275	529
FI	0.11	0.09	0.05	0.06	0.41	0.21	0.06	0.00	44	89	84
FR	0.17	0.28	0.11	0.11	2.20	3.13	0.80	0.11	286	459	661
HR	0.29	0.18	0.13	0.11	0.20	0.09	0.04	0.00	13	20	24
HU	0.34	0.13	0.33	0.23	0.54	0.13	0.28	0.03	32	36	60
IE	0.40	0.37	0.32	0.15	0.20	0.18	0.12	0.00	12	28	41
IT	0.23	0.10	0.03	0.13	2.93	0.60	0.16	0.10	215	324	527
LT	0.63	0.16	0.10	0.21	0.39	0.03	0.05	0.01	12	9	37
LU	0.28	0.19	0.44	0.09	0.09	0.01	0.06	0.00	5	8	8
LV	0.47	0.34	0.08	0.29	0.17	0.05	0.06	0.01	11	7	27
NL	0.33	0.37	0.17	0.12	1.21	0.67	0.40	0.02	71	114	170
NO	0.21	0.29	0.14	0.13	1.08	1.00	0.33	0.01	96	150	112
PL	0.52	0.18	0.00	0.25	2.51	0.42	0.00	0.15	96	126	160
PT	0.25	0.37	0.22	0.29	0.31	0.25	0.15	0.01	23	49	75
RO	0.40	0.39	0.00	0.42	0.80	0.27	0.00	0.10	35	46	64
SE	0.17	0.41	0.40	0.13	1.04	1.79	1.18	0.04	120	136	127
SI	0.26	0.23	0.43	0.11	0.18	0.06	0.04	0.00	9	14	14
SK	0.47	0.36	0.52	0.15	0.81	0.15	0.28	0.02	25	29	28
UK	0.31	0.34	0.33	0.14	3.54	3.60	2.82	0.08	274	356	389
Total					28.15	20.04	11.11	1.16	2247	3224	4327

C.2 Market outcomes

Table C.2: Regional energy efficiency capacities [GW]

	Level	Accumulated investments						
Region	2015	2020	2025	2030	2035	2040	2045	2050
Britain	10.5	0.0	0.5	0.5	0.5	0.5	0.4	0.4
France	6.2	3.6	3.6	3.6	3.6	3.6	3.6	3.4
Benelux	4.2	2.4	3.3	3.3	3.3	3.3	3.3	3.2
Germany-N	5.2	0.6	1.0	2.1	2.1	2.1	2.0	1.8
Germany-S	4.3	0.8	1.2	2.1	2.1	2.1	2.0	1.8
Scandinavia	7.7	0.0	0.0	0.0	0.4	0.4	0.4	0.3
Iberia	4.2	4.3	4.3	4.3	4.3	4.3	4.3	4.2
Alpine	2.3	3.3	4.3	4.3	4.3	4.3	4.3	4.2
Italy	3.8	4.7	4.7	4.7	4.7	4.7	4.7	4.6
Eastern Europe-NW	5.9	3.5	3.5	3.5	3.5	3.5	3.5	3.4
Eastern Europe-NE	1.0	2.2	3.6	4.7	5.6	5.8	5.8	5.3
Eastern Europe-SW	1.6	3.6	4.5	4.5	4.5	4.5	4.5	4.4
Eastern Europe-SE	3.6	3.0	4.1	4.1	5.2	5.2	5.2	5.0

Note: The 2015 value is the initial level of energy efficiency based on the approximation described in Section 3.4. The values for the years 2020–2050 show the accumulated investments. Note that the latter values already account for depreciation.

Table C.3: Change of relative regional equilibrium prices with responsive demand (compared to 2015)

	2015	2020	2025	2030	2035	2040	2045	2050
Britain	1.00	0.95	0.91	0.90	0.95	0.90	0.91	0.89
France	0.97	0.85	0.89	1.00	0.94	0.94	0.91	0.93
Benelux	1.00	0.90	0.96	0.96	0.94	0.95	0.92	0.93
Germany-N	1.00	1.00	0.96	0.95	0.94	0.93	0.93	0.92
Germany-S	1.00	1.00	0.95	0.96	0.93	0.93	0.92	0.91
Scandinavia	1.00	0.92	0.91	0.88	0.87	0.93	0.91	0.91
Iberia	1.00	0.98	0.94	0.97	0.94	0.93	0.93	0.92
Alpine	1.00	0.83	0.89	1.00	0.93	0.96	0.93	0.90
Italy	1.00	1.00	0.92	0.97	0.96	0.94	0.93	0.93
Eastern Europe-NW	1.00	1.00	0.93	0.88	0.92	0.92	0.91	0.91
Eastern Europe-NE	0.93	0.76	0.65	0.77	0.83	0.88	0.90	0.90
Eastern Europe-SW	1.00	0.81	1.00	1.00	0.83	0.88	0.94	0.96
Eastern Europe-SE	1.00	0.65	0.67	0.70	0.78	0.85	0.91	0.91

Note: The change in relative prices in 2015 for some regions is caused solely by adjustment due to short-term demand response and only leads to price changes in France and Eastern Europe-NE.

Appendix D

Appendix to Chapter 4

D.1 Sample of models

Table D.1: Overview of sample of models

Acronym	Model Full Name	Host Institution	Reference
Balmorel	A Model for Analyses of the Electricity and CHP Markets in the Baltic Sea Region	Elkraft System	Ravn et al. (2001)
DESSTINEE	Demand for Energy Services, Supply and Transmission in Europe	Imperial College London	Boßmann and Staffell (2015)
DIETER	Dispatch and Investment Evaluation Tool with Endogenous Renewables	German Institute for Economic Research, Berlin	Zerrahn and Schill (2017)
DIMENSION	A Dispatch and Investment Model for European Electricity Markets	ewi Energy Research & Scenarios	Richter (2011)
Dispa-SET 2.0	Unit commitment and power dispatch model	Institute for Energy and Transport, Joint Research Centre	Hidalgo González et al. (2014)
E2M2s	European Electricity Market Model	Institute of Energy Economics and Rational Energy Use (IER), University of Stuttgart	IER (2013)
ELMOD	Spatial Optimization Model of the Electricity Sector	DIW Berlin	Egerer et al. (2014)
Eltramod	Electricity Transshipment Model	Chair of Business Management, esp. Energy Economics, TU Dresden	Chair of Business, ESP Energy Economics (2012)
EMCAS	Electricity Market Complex Adaptive System	Argonne National Laboratory	Conzelmann et al. (2005)
EMLab	Energy Modelling Laboratory	TU Delft	Richstein et al. (2014); Chappin (2011)
EMMA	European Electricity Market Model	Potsdam Institute for Climate Impact Research / Neon Neue Energieökonomik	Hirth (2016)
EMPIRE	European Model for Power System Investment with Renewable Energy	Norwegian University of Science and Technology	Skar et al. (2016)
EnergyPLAN		Aalborg University	Lund (2015)
EU-REGEN	EU Regional Economy, Greenhouse Gas, and Energy Model	ifo Institute	see Chapter 1
evrys	–	Chair of Renewable and Sustainable Energy Systems, Technical University of Munich	Huber (2017)
GENESYS	Genetic Optimization of a European Energy Supply System	RWTH Aachen University	Bussar et al. (2017)
Haiku	Electricity Market Model	Resources for the Future	Paul et al. (2009)
HECTOR	Hourly Electricity, CCS and Transmission Optimizer	Institute for Future Energy Consumer Needs and Behavior, RWTH Aachen University	Lohwasser and Madlener (2009)
IKARUS		Institute of Energy Research at Research Centre Juelich	Markewitz et al. (1996)
LEAP	Long-range Energy Alternatives Planning System	Stockholm Environment Institute	Heaps (2012)
LIBEMOD	Liberalisation Model for the European Energy Markets	CREE Frisch Centre	Aune et al. (2015)
LIMES-EU	Long Term Investment Model for the Electricity Sector of Europe	Potsdam Institute for Climate Impact Research	Nahmmacher et al. (2014)
MARKAL/ TIMES	Market Allocation Model/The Integrated MARKAL-EFOM System	Energy Technology Systems Analysis Program, International Energy Agency	Loulou et al. (2005)

Continued on next page

Table D.1 – *Continued from previous page*

Acronym	Model Full Name	Host Institution	Reference
MESSAGE	Model for Energy Supply Strategy Alternatives and their General Environmental Impact	International Institute for Applied Systems Analysis	IAEA (2016); Messner and Strubegger (1995)
METIS	Modeling the European Power System	Directorate-General for Energy of the European Commission	Chammas et al. (2017)
MultiMod		German Institute for Economic Research, Berlin	Huppmann and Egging (2014)
NEMO	National Electricity Market Optimiser	Centre for Energy and Environmental Markets, University of New South Wales	Elliston et al. (2013)
NEMS	National Energy Modeling System	U.S. Energy Information Agency	EIA (2014)
OSeMOSYS	Open Source Energy Modeling System	KTH Royal Institute of Technology	Howells et al. (2011)
PERSEUS	Program Package for Emission Reduction Strategies in Energy Use and Supply	Institute for Industrial Production, Karlsruhe Institute of Technology (KIT)	Eßer-Frey (2012); Möst and Fichtner (2010)
PLEXOS	Integrated Energy Model	Energy Exemplar	Edmunds (2014)
POLES	Prospective Outlook on Long-term Energy Systems	EDDEN laboratory, University of Grenoble-CNRS	Kitous et al. (2010); Criqui et al. (2015)
PRIMES	Price-Induced Market Equilibrium System	Energy-Economy-Environment Modelling Laboratory (E3MLab), National Technical University of Athens	E3MLab (2017)
PyPSA	Python for Power System Analysis	Frankfurt Institute for Advanced Studies	Brown et al. (2018)
REMix	Renewable Energy Mix	Institute of Engineering Thermodynamics, German Aerospace Centre	Scholz (2012); Gils et al. (2017)
REMod-D	Renewable Energy Model - Deutschland	Fraunhofer Institute for Solar Energy System	Henning and Palzer (2014)
stELMOD	Stochastic ELMOD	German Institute for Economic Research, Berlin	Abrell and Kunz (2015)
Swissmod	Model of the Swiss Electricity Market	Research Center for Sustainable Energy and Water Supply, University of Basel	Schlecht and Weigt (2014, 2015)
SWITCH	Solar and Wind energy Integrated with Transmission and Conventional sources	Renewable and Appropriate Energy Laboratory, UC Berkeley	Fripp (2008)
urbs	–	Chair of Renewable and Sustainable Energy Systems, Technical University of Munich	Schaber et al. (2012); Huber et al. (2012)

D.2 Model criteria and features

Model-Theoretic Specifications

Analytical method

input-output/spreadsheet/
simulation/optimization/
economic equilibrium/econometric/
agent-based/multi-criteria/other

Programming technique

linear/mixed-integer/dynamic/
fuzzy-logic/other non-linear

Model perspective

top-down/bottom-up/hybrid

Endogenous features

generation capacity investment/
storage capacity investment/
transmission capacity inverstment/
generation dispatch/storage dispatch/
load flows/trade flows/
demand/technological learning/
market prices/emission rates and prices

Representation of uncertainty and risk

yes/no

Representation of acceptance

yes/no

Figure D.1: Model criteria and features within the category "Model-Theoretic Specifications"

Market Representation

Energy sectoral coverage

heat/power-to-X/
transportation, mobility

Represented markets

spot market/balancing market/
capacity market/futures market

Demand representation

short-term/long-term

Policy constraints

CO_2 emissions constraints/taxes/
technology restrictions/RES quota/
RES subsidy/CO_2 trading/market design*

**Market design* refers to organizational structures ranging from widely existing models discussed in Barroso et al. (2005) to new types like capacity markets.

Figure D.2: Model criteria and features within the category "Market Representation"

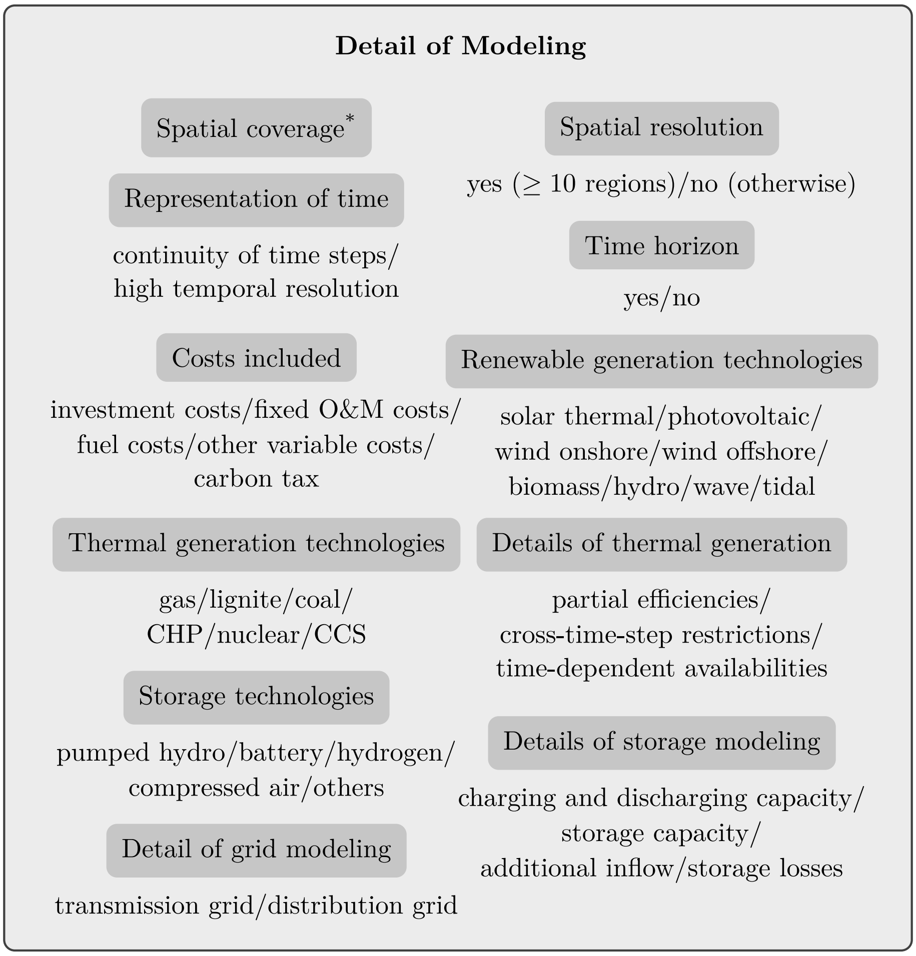


Figure D.3: Model criteria and features within the category "Detail of Modeling"

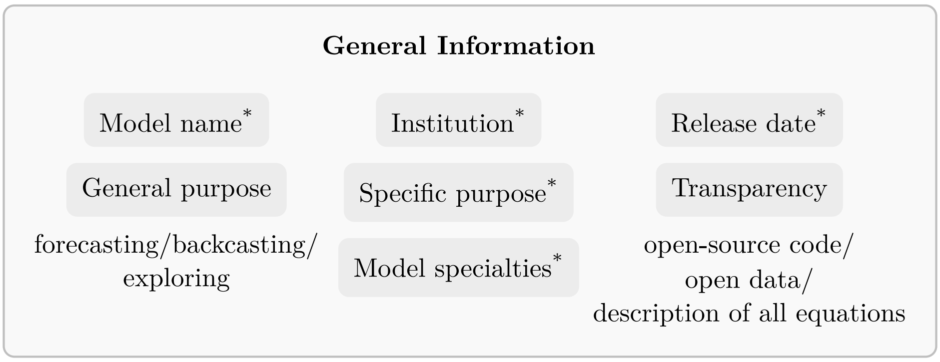


Figure D.4: Model criteria and features within the category "General Information"

D.3 Examples of analysis steps

How-To (1): Model analysis

Consider a generic model M_x. Analyzing the model using a subset of criteria is done in the following way:

- *Representation of acceptance:* Model M_x does not take into account the acceptance of the stakeholders. Since this is a binary criterion, the answer is simply “no”.
- *Detail of grid modeling:* This is a multiple-choice criterion. Model M_x has a simple depiction of the transmission grid (“yes”), but no representation of the distribution grid (“no”).
- *Thermal generation technologies:* This is also a multiple-choice criterion. Model M_x is capable of including gas, coal, lignite, combined heat and power generators, and nuclear power plants (“yes”) but no carbon capture and storage plants (“no”).

How-To (2): Policy questions analysis

Consider the question Q_{12}: “How does the cost-optimal grid expansion deviate if acceptance is taken into account?”. Analyzing the policy question using a subset of criteria is done in the following way:

- *Representation of acceptance:* This model feature is required to answer the policy question Q_{12}, so it belongs to the set of mandatory features.
- *Detail of grid modeling:* Usually, the lack of acceptance hinders or delays the construction of new overhead transmission lines. The distribution grid being mostly underground, its expansion is usually not affected by the acceptance. Thus, the depiction of the transmission grid is a mandatory feature, whereas the representation of the distribution grid is a facultative feature.
- *Thermal generation technologies:* Conventional power plants should be included to obtain a realistic power flow, yet this is not the main goal of the study. Besides, no single technology is particularly crucial: the modeling of two or three technologies among gas, coal, lignite, combined heat and power generators, and nuclear power plants should be sufficient. Hence, they belong to the complementary features. The CO_2 emissions are probably not relevant for Q_{12}, so the modeling of carbon capture and storage plants is rather a facultative feature.

How-To (3): Model-question gap quantification

Consider the generic model $\mathrm{M_x}$, the policy question $\mathrm{Q_{12}}$, and the three criteria used before (representation of acceptance, detail of grid modeling, and thermal generation technologies). The model-question gap $d_{M_x,Q_{12}}$ is calculated in the following way:

- The set of mandatory features has only two elements (representation of acceptance and of the transmission grid), so $|S_{++}^{Q_{12}}| = 2$. Among them, only the latter is modeled in $\mathrm{M_x}$, hence $|S_{++}^{Q_{12}} \cap S^{M_x}| = 1$ and $|S_{++}^{Q_{12}} \cap \overline{S^{M_x}}| = 1$.
- The set of complementary features has five elements (modeling of gas, coal, lignite, combined heat and power generators, and nuclear power plants), so $|S_{+}^{Q_{12}}| = 5$. All of them are modeled in $\mathrm{M_x}$, hence $|S_{+}^{Q_{12}} \cap S^{M_x}| = 5$.
- There are two facultative features (representation of the distribution grid and the modeling of carbon capture and storage plants). None of them are available in the model $\mathrm{M_x}$. This set has no impact on the model-question gap anyway.

All in all, we obtain: $d_{M_x,Q_{12}} = 1 - \dfrac{2 \cdot 1 + 5 - 2 \cdot 1}{2 \cdot 2 + 5} \approx 0.44$.

How-To (4): Feature gap quantification

The feature gap should be used for large sets of models and policy questions. However, we can still apply the formula in Equation (4.2) to the model features used before for $\mathrm{M} = \{\mathrm{M_x}\}$ and $\mathrm{Q} = \{\mathrm{Q_{12}}\}$.

- For f = representation of acceptance, the feature gap is critical: $d_f^{M,Q} = \dfrac{|S_{++}^{Q_{12}}(f)|}{|Q|} - \dfrac{|S^{M_x}(f)|}{|M|} = \dfrac{1}{1} - \dfrac{0}{1} = 1.$
- Detail of grid modeling: $d_{transmission}^{M,Q} = d_{distribution}^{M,Q} = 0$ for different reasons. The first feature is both mandatory and included in $\mathrm{M_x}$, the second is neither mandatory nor implemented.
- Thermal generation technologies: For the features gas, coal, lignite, combined heat and power generators, and nuclear power plants, $d_f^{M,Q} = -1$ because all are implemented but not mandatory. For the modeling of carbon capture and storage plants, $d_{CCS}^{M,Q} = 0$.

D.4 Description of the energy policy issues cluster

This section contains detailed information on the model-oriented categories of the EPIC.

Object dimension - instruments

- *Market-based instruments:* are instruments targeting at the price or quantity of an externality or element of the energy system. Examples comprise volume-controlling instruments as the EU ETS or national CO_2 taxes.[1]
- *Promotion of investments:* are instruments aiming at the direct promotion of investments. This can range from loan subsidies and R&D funding to technology-specific tariffs, for example, feed-in tariffs for RES.
- *Command-and-control instruments:* are instruments that enforce measures like technology bans (i.e., nuclear phase-out) or emission standards.
- *Soft instruments:* are instruments that are non-binding and have no direct impact on the market outcome. They can comprise, for example, voluntary obligations (e.g., green pricing) and information policies (e.g. energy label).

Object dimension - energy system design

- *Electricity sector configuration:* aims at identifying the optimal technology-mix with respect to a specific decarbonization target.
- *Sectoral integration:* comprises the optimal level of integrating the electricity sector with other energy sectors like heat, mobility, and industry.
- *Regional integration:* captures the preferable degree of (geographic) market coupling. This can comprise whether interconnectivity between regions is more preferable than an autonomous and highly decentralized energy systems.

Evaluation perspective

- *System costs:* the sole objective of finding the cost-efficient market outcome.
- *Distributional effects:* the equality of welfare or costs distribution among heterogeneous regions or agents is considered in the evaluation of a transformation path.
- *Energy independence:* the degree to which a region depends on electricity or commodity imports is explicitly considered.

[1] In the context of RES, this category also captures RES quotas and green certificates.

- *Supply security and resilience:* consequences from irregularities in terms of electricity or commodity supply and the intermittent nature of RES are taken into account when analyzing different market outcomes.
- *Acceptance:* the acceptance of individual technologies or entire transformation paths is considered for identifying the equilibrium market outcome.
- *Path dependencies:* the costs of locking an energy system into a subset of technologies due to, for instance, the underlying infrastructure, are considered in the evaluation of a transformation path.

D.5 Feature gap results

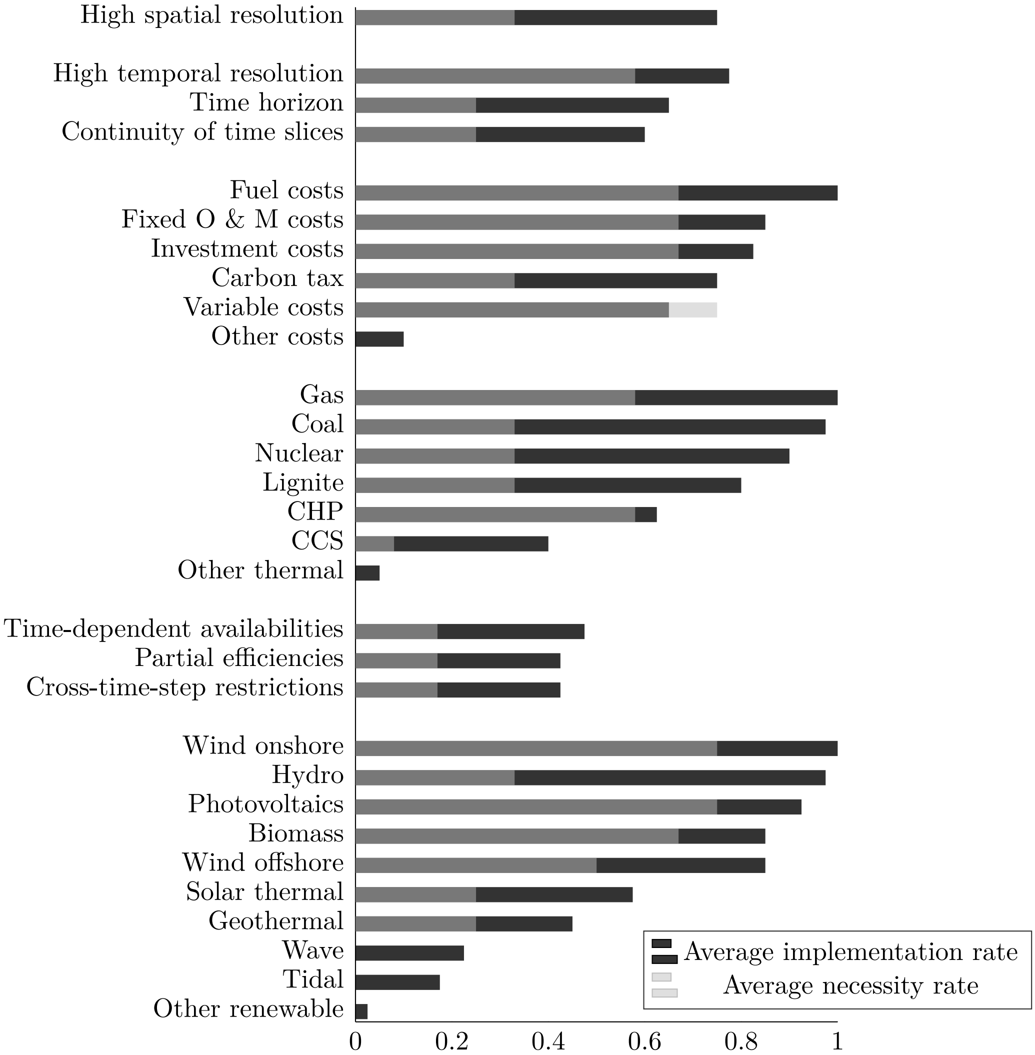


Figure D.5: Average implementation rate and average necessity rate for space and time representation, costs, conventional and renewable technologies, and storage modeling features

Note: The bars are superposed, so that the black bars are only visible if the implementation rate exceeds the necessity rate. Otherwise, critical discrepancies exist and are colored in light gray.

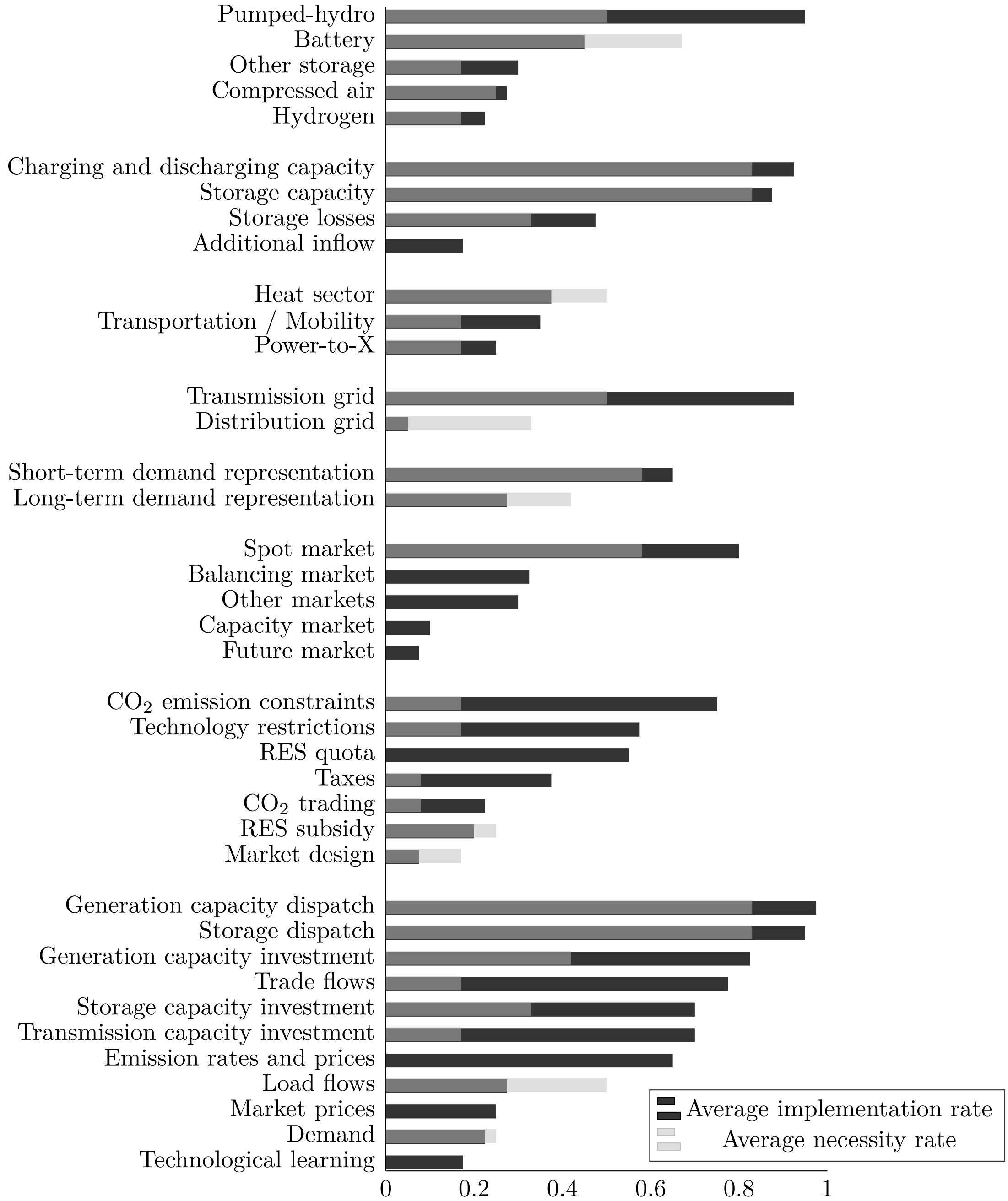


Figure D.6: Average implementation rate and average necessity rate for sector coupling, grid representation, demand, markets, policy constraints and key endogenous features

Note: The bars are superposed, so that the black bars are only visible if the implementation rate exceeds the necessity rate. Otherwise, critical discrepancies exist and are colored in light gray.

Bibliography

Abatzoglou, J. T. and A. P. Williams (2016). Impact of anthropogenic climate change on wildfire across western US forests. *Proceedings of the National Academy of Sciences 113*(42), 11770–11775.

Abrell, J. and F. Kunz (2015). Integrating intermittent renewable wind generation - A stochastic multi-market electricity model for the European electricity market. *Networks and Spatial Economics 15*(1), 117–147.

Abrell, J. and S. Rausch (2016). Cross-country electricity trade, renewable energy and European transmission infrastructure policy. *Journal of Environmental Economics and Management 79*, 87–113.

Acemoglu, D., P. Aghion, L. Bursztyn, and D. Hemous (2012). The environment and directed technical change. *American Economic Review 102*(1), 131–166.

Allcott, H. and M. Greenstone (2017). Measuring the welfare effects of residential energy efficiency programs. *NBER Working Paper 23386*.

Ang, B. and B. Su (2016). Carbon emission intensity in electricity production: A global analysis. *Energy Policy 94*, 56–63.

Anthoff, D. and R. S. Tol (2013). The uncertainty about the social cost of carbon: A decomposition analysis using fund. *Climatic Change 117*(3), 515–530.

Asane-Otoo, E. (2016). Competition policies and environmental quality: Empirical analysis of the electricity sector in OECD countries. *Energy Policy 95*, 212 – 223.

Assemblée Nationale (2015). *Projet de loi: Relatif à la transition énergétique pour la croissance verte*. Paris.

Auffhammer, M. and E. T. Mansur (2014). Measuring climatic impacts on energy consumption: A review of the empirical literature. *Energy Economics 46*, 522–530.

Aune, F. R., R. Golombek, and H. H. Le Tissier (2015). Phasing out nuclear in Europe. *CREE Working Paper 05/2015*.

Baier, S. L. and J. H. Bergstrand (2004). Economic determinants of free trade agreements. *Journal of international Economics 64*(1), 29–63.

Baldini, M. and A. Trivella (2018). Modelling of electricity savings in the Danish households sector: From the energy system to the end-user. *Energy Efficiency 11*(7), 1563–1581.

Barrett, S. (1994). Self-enforcing international environmental agreements. *Oxford Economic Papers 46*, 878–894.

Barroso, L. A., T. H. Cavalcanti, P. Giesbertz, and K. Purchala (2005). Classification of electricity market models worldwide. In *CIGRE/IEEE PES, 2005. International Symposium*, pp. 9–16. IEEE.

Batlle, C., I. J. Pérez-Arriaga, and P. Zambrano-Barragán (2012). Regulatory design for RES-E support mechanisms: Learning curves, market structure, and burden-sharing. *Energy Policy 41*, 212–220.

Bazmi, A. A. and G. Zahedi (2011). Sustainable energy systems: Role of optimization modeling techniques in power generation and supply - A review. *Renewable and Sustainable Energy Reviews 15*(8), 3480–3500.

Beestermöller, R. (2017). *Die Energienachfrage privater Haushalte und ihre Bedeutung für den Klimaschutz: Volkswirtschaftliche Analysen zur deutschen und europäischen Klimapolitik mit einem technologiefundierten Allgemeinen Gleichgewichtsmodell.* Ph. D. thesis, University of Stuttgart, Stuttgart.

Bhattacharyya, S. C. and G. R. Timilsina (2010). A review of energy system models. *International Journal of Energy Sector Management 4*(4), 494–518.

Blanford, G. J., J. H. Merrick, J. E. Bistline, and D. T. Young (2018). Simulating annual variation in load, wind, and solar by representative hour selection. *The Energy Journal 39*(3), 189–212.

Blanford, G. J., J. H. Merrick, and D. Young (2014). A Clean Energy Standard Analysis with the US-REGEN Model. *The Energy Journal 35*, 137–164.

BMWi (2010). Energiekonzept: Für eine umweltschonende, zuverlässige und bezahlbare Energieversorgung. Technical report, Bundesministerium für Wirtschaft und Energie (BMWi), Berlin.

Böcher, M. (2012). A theoretical framework for explaining the choice of instruments in environmental policy. *Forest Policy and Economics 16*, 14–22.

Boden, T., R. Andres, and G. Marland (2017). Global, regional, and national fossil-fuel CO_2 emissions (1751 - 2015) (v. 2017). *URL: https://cdiac.ess-dive.lbl.gov/ (accessed: February 5, 2019).*

Böhringer, C., N. Rivers, et al. (2018). The energy efficiency rebound effect in general equilibrium. *Oldenburg Discussion Papers in Economics V-410-18*.

Böhringer, C. and K. E. Rosendahl (2010). Green promotes the dirtiest: On the interaction between black and green quotas in energy markets. *Journal of Regulatory Economics 37*(3), 316–325.

Boilley, A. and L. Wald (2015). Comparison between meteorological re-analyses from ERA-Interim and MERRA and measurements of daily solar irradiation at surface. *Renewable Energy 75*, 135–143.

Borenstein, S. (2008). The market value and cost of solar photovoltaic ectricity production. *Center for the Study of Energy Markets Working Paper 176*.

Borenstein, S. (2012). The private and public economics of renewable electricity generation. *Journal of Economic Perspectives 26*(1), 67–92.

Borenstein, S. (2015). A microeconomic framework for evaluating energy efficiency rebound and some implications. *The Energy Journal 36*(1), 1–21.

Borenstein, S., J. Bushnell, and C. R. Knittel (1999). Market power in electricity markets: Beyond concentration measures. *The Energy Journal 20*(4), 65–88.

Boßmann, T. and I. Staffell (2015). The shape of future electricity demand: Exploring load curves in 2050s Germany and Britain. *Energy 90*(2), 1317–1333.

Bréchet, T., F. Gerard, and H. Tulkens (2011). Efficiency vs. stability in climate coalitions: A conceptual and computational appraisal. *The Energy Journal 31*(1), 49–75.

Brovold, S. H., C. Skar, and O. B. Fosso (2014). Implementing hydropower scheduling in a European expansion planning model. *Energy Procedia 58*, 117–122.

Brown, T., J. Hörsch, and D. Schlachtberger (2018). PyPSA: Python for Power System Analysis. *Journal of Open Research Software 6*(4), 1–15.

Bründlicher, T., J. E. König, O. Frank, D. Gründig, C. Jugel, P. Kraft, O. Krieger, S. Mischinger, P. Prein, H. Seidl, S. Siegemung, C. Stolte, M. Teichmann, J. Willke, and M. Wolke (2017). dena Leitstudie - Integrierte Energiewende. Technical report, Deutsche Energie-Agentur GmbH (dena), Berlin.

Bruninx, K., D. Orlic, D. Couckuyt, N. Grisey, B. Betraoui, T. Anderski, Y. Surmann, N. T. Franck, G. Keane, B. Hickman, D. Huertas-Hernando, M. Wilk, and R. Jankowski

(2015). Modular development plan of the Pan-European transmission system 2050: Data sets of scenarios for 2050. Technical report, The e-HIGHWAY 2050 Project.

Bundesnetzagentur (2012). Netzenwicklungsplan Strom 2012. Technical report, Bundesnetzagentur, Berlin.

Bundesnetzagentur (2015). EnLAG-Monitoring: Stand des Ausbaus nach dem Energieleitungsausbaugesetz zum ersten Quartal 2015. Technical report, Bundesnetzagentur, Berlin.

Bussar, C., P. Stöcker, L. Moraes, K. Jacqué, H. Axelsen, and D. Sauer (2017). The long-term power system evolution – First optimisation results. *Energy Procedia 135*, 347–357.

Cannon, D., D. Brayshaw, J. Methven, P. Coker, and D. Lenaghan (2015). Using reanalysis data to quantify extreme wind power generation statistics: A 33 year case study in Great Britain. *Renewable Energy 75*, 767–778.

Cao, K.-K., F. Cebulla, J. J. G. Vilchez, B. Mousavi, and S. Prehofer (2016). Raising awareness in model-based energy scenario studies - A transparency checklist. *Energy, Sustainability and Society 6*(1), 28.

Carraro, C. and D. Siniscalco (1992). The international dimension of environmental policy. *European Economic Review 36*(2), 379–387.

Carraro, C. and D. Siniscalco (1993). Strategies for the international protection of the environment. *Journal of Public Economics 52*(3), 309–328.

Chair of Business, ESP Energy Economics (2012). Eltramod: Electricity Transhipment Model. Technical report, Technical University of Dresden.

Chakravarty, D., S. Dasgupta, and J. Roy (2013). Rebound effect: How much to worry? *Current Opinion in Environmental Sustainability 5*(2), 216–228.

Chammas, M., J. Fauque, and L. Fournié (2017). METIS Technical Note T5. Technical report, European Commission.

Chan, N. W. and K. Gillingham (2015). The microeconomic theory of the rebound effect and its welfare implications. *Journal of the Association of Environmental and Resource Economists 2*(1), 133–159.

Chander, P. and H. Tulkens (1995). A core-theoretic solution for the design of cooperative agreements on transfrontier pollution. *International Tax and Public Finance 2*(2), 279–293.

Chappin, E. (2011). *Simulating energy transitions.* Ph. D. thesis, Delft University of Technology, Delft.

Chiabrando, R., E. Fabrizio, and G. Garnero (2009). The territorial and landscape impacts of photovoltaic systems: Definition of impacts and assessment of the glare risk. *Renewable and Sustainable Energy Reviews 13*(9), 2441–2451.

Connolly, D., H. Lund, B. V. Mathiesen, and M. Leahy (2010). A review of computer tools for analysing the integration of renewable energy into various energy systems. *Applied Energy 87*(4), 1059–1082.

Conzelmann, G., G. Boyd, V. Koritarov, and T. Veselka (2005). Multi-agent power market simulation using EMCAS. In *IEEE Power Engineering Society General Meeting, 2005*, pp. 2829–2834 Vol. 3. IEEE.

Cook, J., D. Nuccitelli, S. A. Green, M. Richardson, B. Winkler, R. Painting, R. Way, P. Jacobs, and A. Skuce (2013). Quantifying the consensus on anthropogenic global warming in the scientific literature. *Environmental Research Letters 8*(2), 024024.

Cook, J., N. Oreskes, P. T. Doran, W. R. L. Anderegg, B. Verheggen, E. W. Maibach, J. S. Carlton, S. Lewandowsky, A. G. Skuce, S. A. Green, D. Nuccitelli, P. Jacobs, M. Richardson, B. Winkler, R. Painting, and K. Rice (2016). Consensus on consensus: A synthesis of consensus estimates on human-caused global warming. *Environmental Research Letters 11*(4), 048002.

Coppens, C., H. Gordijn, M. Piek, P. Ruyssenaars, J.-J. Schrander, P. d. Smet, R. Swart, M. Hoogwijk, M. Papalexandrou, E. d. Visser, J. Horalek, P. Kurfürst, F. P. Jensen, B. S. Petersen, M. Harfoot, R. Milego, N.-E. Clausen, and G. Giebel (2009). Europe's onshore and offshore wind energy potential: An assessment of environmental and economic constraints. Technical report, European Environment Agency (EEA), Copenhagen.

Crew, M. A., C. S. Fernando, and P. R. Kleindorfer (1995). The theory of peak-load pricing: A survey. *Journal of Regulatory Economics 8*(3), 215–248.

Criqui, P., S. Mima, P. Menanteau, and A. Kitous (2015). Mitigation strategies and energy technology learning: An assessment with the POLES model. *Technological Forecasting and Social Change 90*(Part A), 119–136.

d'Aspremont, C. and J. J. Gabszewicz (1986). *On the stability of collusion: New developments in the analysis of market structure.* Cambridge: MIT Press.

d'Aspremont, C., A. Jacquemin, J. J. Gabszewicz, and J. A. Weymark (1983). On the stability of collusive price leadership. *The Canadian Journal of Economics 16*(1), 17–25.

Davis, L. W. (2011). The effect of power plants on local housing values and rents. *Review of Economics and Statistics 93*(4), 1391–1402.

Davis, M. and M. Maschler (1965). The kernel of a cooperative game. *Naval Research Logistics 12*(3), 223–259.

de Joode, J., O. Ozdemir, K. Veum, A. van der Welle, G. Miglavacca, A. Zani, and A. L'Abbate (2011). Development of regional and Pan-European guidelines for more efficient integration of renewable energy into future infrastructure 'SUSPLAN'. Technical report, The SUSPLAN Project.

Deane, J., A. Chiodi, M. Gargiulo, and B. P. Ó Gallachóir (2012). Soft-linking of a power systems model to an energy systems model. *Energy 42*(1), 303–312.

DeCarolis, J. F. (2011). Using modeling to generate alternatives (MGA) to expand our thinking on energy futures. *Energy Economics 33*(2), 145–152.

DeCarolis, J. F., K. Hunter, and S. Sreepathi (2012). The case for repeatable analysis with energy economy optimization models. *Energy Economics 34*(6), 1845–1853.

Després, J., N. Hadjsaid, P. Criqui, and I. Noirot (2015). Modelling the impacts of variable renewable sources on the power sector: Reconsidering the typology of energy modelling tools. *Energy 80*, 486–495.

Deutsch, M., F. Ess, J. Hobohm, V. Rits, M. Schlesinger, and S. Strassburg (2011). Analysis and comparison of relevant mid- and long-term energy scenarios for EU and their key underlying assumptions. Technical report, Prognos AG.

Drechsel, J. and A. Kimms (2010). Computing core allocations in cooperative games with an application to cooperative procurement. *International Journal of Production Economics 128*(1), 310–321.

Dröes, M. I. and H. R. Koster (2016). Renewable energy and negative externalities: The effect of wind turbines on house prices. *Journal of Urban Economics 96*, 121–141.

E3MLab (2017). PRIMES Model Version 6 - Detailed model description. Technical report, National Technical University of Athens, Athens.

EC (2007). An energy policy for Europe. Technical report, European Commission (EC), Brussels.

EC (2011a). Energy roadmap 2050. Technical report, European Commission (EC), Brussels.

EC (2011b). Impact assessment: A roadmap for moving to a competitive low carbon economy in 2050. Technical report, European Commission (EC), Brussels.

EC (2013a). EU energy, transport and GHG emissions trends to 2050: Reference scenario 2013. Technical report, European Commission (EC), Brussels.

EC (2013b). On the future of carbon capture and storage in Europe. Technical report, European Commission (EC), Brussels.

EC (2014). Impact assessment: A policy framework for climate and energy in the period from 2020 to 2030. Technical report, European Commission (EC), Brussels.

EC (2015). Energy union package: A framework strategy for a resilient energy union with a forward-looking climate change policy. Technical report, European Commission (EC), Brussels.

EC (2016). Clean Energy for all Europeans - Annex: Accelerating clean energy in buildings. Technical report, European Commission (EC), Brussels.

EC (2017). Analysis of the use of auction revenues by the member states. Technical report, European Commission (EC), Brussels.

EC (2018). A clean planet for all: A European strategic long-term vision for a prosperous, modern, competitive and climate neutral economy. Technical report, European Commission (EC), Brussels.

Edenhofer, O., C. Flachsland, M. Jakob, and K. Lessmann (2013). The atmosphere as a global commons: Challenges for international cooperation and governance. *MCC Working paper 1-2013*.

Edenhofer, O., L. Hirth, B. Knopf, M. Pahle, S. Schlömer, E. Schmid, and F. Ueckerdt (2013). On the economics of renewable energy sources. *Energy Economics 40*(Supplement 1), 12–23.

Edmunds, R. (2014). PLEXOS Working Document. Technical report, Univeristy of Leeds.

EEA (2018). EU Emissions Trading System (ETS) data viewer. *URL: https://www.eea.europa.eu/data-and-maps (accessed: July 31, 2018).*

Egerer, J., C. Gerbaulet, R. Ihlenburg, F. Kunz, B. Reinhard, C. von Hirschhausen, A. Weber, and J. Weibezahn (2014). Electricity sector data for policy-relevant modeling: Data documentation and applications to the German and European electricity markets. Technical report, German Institute for Economic Research.

Egerer, J., C. von Hirschhausen, J. Weibezahn, and C. Kemfert (2015). Energiewende und Strommarktdesign: Zwei Preiszonen für Deutschland sind keine Lösung. *DIW Wochenbericht 9*, 183–190.

Egerer, J., J. Weibezahn, and H. Hermann (2016). Two price zones for the German electricity market — Market implications and distributional effects. *Energy Economics 59*, 365–381.

EIA (2014). The electricity market module of the national energy modeling system: Model documentation. Technical report, US Energy Information Administration (EIA), US, Washington, DC.

Elbersen, B., I. Startisky, G. Hengeveld, and M.-J. Schelhass (2012). Atlas of EU biomass potentials: Spatially detailed and quantified overview of EU biomass potential taking into account the main criteria determining biomass availability from different sources. Technical report, The Biomass Futures Project.

Elliston, B., I. Macgill, and M. Diesendorf (2013). Least cost 100% renewable electricity scenarios in the Australian national electricity market. *Energy Policy 59*, 270–282.

Enerdata (2018). Odyssee database. *URL http://www.indicators.odyssee-mure.eu (accessed: September 7, 2018).*

Energy Exemplar (2018). Plexos for power systems. Technical report, Energy Exemplar, North Adelaide.

ENTSO-E (2014a). 10-year network development plan 2014. Technical report, European Network of Transmission System Operators for Electricity (ENTSO-E), Brussels.

ENTSO-E (2014b). Hourly load values for all countries for a specific month. *URL: https://www.entsoe.eu/db-query/consumption/mhlv-all-countries-for-a-specific-month (accessed: December 7, 2014).*

ENTSO-E (2014c). Net Transfer Capacity (NTC) values summer 2010. *URL: https://www.entsoe.eu/publications/market-reports/ntc-values/Pages/default.aspx (accessed: November 30, 2014).*

EPRI (2014). Comments of the Electric Power Research Institute on Environmental Protection Agency: Carbon pollution emission guidelines for existing stationary sources: Electric utility generating units. Technical report, Electric Power Research Institute (EPRI), Pao Alto.

Eßer-Frey, A. (2012). *Analyzing the regional long-term development of the German power system using a nodal pricing approach.* Ph. D. thesis, Karlsruhe Institute of Technology, Karlsruhe.

Eurostat (2014). Supply, transformation and consumption of electricity: Annual data. *http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_105a (accessed: January 28, 2015).*

Eurostat (2018). Electricity production capacities for renewables and wastes. *URL: http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_inf_epcrw&lang=en (accessed: August 13, 2018).*

Eyckmans, J. and M. Finus (2009). An almost ideal sharing scheme for coalition games with externalities. *Stirling Economics Discussion Paper 2009-10.*

Fabra, N. and M. Reguant (2014). Pass-through of emissions costs in electricity markets. *The American Economic Review 104*(9), 2872–2899.

Fais, B. (2015). *Modelling policy instruments in energy system models – The example of renewable electricity generation in Germany.* Ph. D. thesis, University of Stuttgart, Stuttgart.

Fischer, C. and R. G. Newell (2008). Environmental and technology policies for climate mitigation. *Journal of Environmental Economics and Management 55*(2), 142–162.

Fischer, W., J.-F. Hake, W. Kuckshinrichs, T. Schröder, and S. Venghaus (2016). German energy policy and the way to sustainability: Five controversial issues in the debate on the “Energiewende”. *Energy 115*, 1580–1591.

Foley, A. M., B. P. Ó Gallachóir, J. Hur, R. Baldick, and E. J. McKeogh (2010). A strategic review of electricity systems models. *Energy 35*(12), 4522–4530.

Fouquet, R. (2016). Path dependence in energy systems and economic development. *Nature Energy 1*(8), 16098.

Fowlie, M., M. Greenstone, and C. Wolfram (2018). Do energy efficiency investments deliver? Evidence from the weatherization assistance program. *The Quarterly Journal of Economics 133*(3), 1597–1644.

Fripp, M. (2008). *Optimal investment in wind and solar power in California.* Ph. D. thesis, University of California, Berkeley.

Fromen, B. (1997). Reducing the number of linear programs needed for solving the nucleolus problem of n-person game theory. *European Journal of Operational Research 98*(3), 626–636.

Frondel, M., N. Ritter, C. M. Schmidt, and C. Vance (2010). Economic impacts from the promotion of renewable energy technologies: The German experience. *Energy Policy 38*(8), 4048–4056.

Fullerton, D. and C. L. Ta (2018). Costs of energy efficiency mandates can reverse the sign of rebound. *Working Paper, URL: http://works.bepress.com/don_fullerton/81/*.

Gambardella, C., M. Pahle, and W.-P. Schill (2016). Do benefits from dynamic tariffing rise? Welfare effects of real-time pricing under carbon-tax-induced variable renewable energy supply. *DIW Discussion Papers 1621*.

Gamble, H. B. and R. H. Downing (1982). Effects of nuclear power plants on residential property values. *Journal of Regional Science 22*(4), 457–478.

Gately, D. (1974). Sharing the gains from regional cooperation: A game theoretic application to planning investment in electric power. *International Economic Review 15*(1), 195–208.

Gerbert, P., P. Herhold, J. Burchardt, S. Schönberger, F. Rechenmacher, A. Kirchner, A. Kemmler, and M. Wünsch (2018). Klimapfade für Deutschland. Technical report, The Boston Consulting Group (BCG), Prognos AG.

Gerbonia, R., D. Grossoa, A. Carpignanoa, and B. Dalla Chiarab (2017). Linking energy and transport models to support policy making. *Energy Policy 111*, 336–345.

Gibbons, S. (2015). Gone with the wind: Valuing the visual impacts of wind turbines through house prices. *Journal of Environmental Economics and Management 72*, 177–196.

Gillies, D. B. (1959). Solutions to general non-zero-sum games. *Contributions to the Theory of Games 4*(40), 47–85.

Gillingham, K., M. J. Kotchen, D. S. Rapson, and G. Wagner (2013). The rebound effect is overplayed. *Nature 493*(7433), 475–476.

Gillingham, K. and K. Palmer (2014). Bridging the energy efficiency gap: Policy insights from economic theory and empirical evidence. *Review of Environmental Economics and Policy 8*(1), 18–38.

Gillingham, K., D. Rapson, and G. Wagner (2016). The rebound effect and energy efficiency policy. *Review of Environmental Economics and Policy 10*(1), 68–88.

Gillingham, K. and J. Sweeney (2010). *Market failure and the structure of externalities: Harnessing renewable energy in electric power systems: Theory, practice, policy.* New York: RFF Press.

Gils, H. C., Y. Scholz, T. Pregger, D. L. de Tena, and D. Heide (2017). Integrated modelling of variable renewable energy-based power supply in Europe. *Energy 123*, 173 – 188.

Golombek, R., S. A. C. Kittelsen, and I. Haddeland (2012). Climate change: Impacts on electricity markets in western Europe. *Climatic Change 113*(2), 357–370.

Golosov, M., J. Hassler, P. Krusell, and A. Tsyvinski (2014). Optimal taxes on fossil fuel in general equilibrium. *Econometrica 82*(1), 41–88.

González-Díaz, J. and E. Sánchez-Rodríguez (2007). A natural selection from the core of a TU game: The core-center. *International Journal of Game Theory 36*(1), 27–46.

Göransson, L., J. Goop, T. Unger, M. Odenberger, and F. Johnsson (2014). Linkages between demand-side management and congestion in the European electricity transmission system. *Energy 69*, 860–872.

Green, R. J. and T.-O. Leautier (2015). Do costs fall faster than revenues? Dynamics of renewables entry into electricity markets. *TSE Working Paper 15-591, revised version 2018.*

Greening, L. A., D. L. Greene, and C. Difiglio (2000). Energy efficiency and consumption – the rebound effect – a survey. *Energy policy 28*(6-7), 389–401.

Grotte, J. H. (1970). *Computation of and observations on the nucleolus, the normalized nucleolus, and the central games.* Ph. D. thesis, Cornell University, Ithaca.

Guajardo, M. and K. Jörnsten (2015). Common mistakes in computing the Nucleolus. *European Journal of Operational Research 241*(3), 931–935.

Guivarch, C. and S. Monjon (2017). Identifying the main uncertainty drivers of energy security in a low-carbon world: The case of Europe. *Energy Economics 64*(Supplement C), 530–541.

Hall, L. M. and A. R. Buckley (2016). A review of energy systems models in the UK: Prevalent usage and categorisation. *Applied Energy 169*, 607–628.

Heaps, C. (2012). Long-range energy alternatives planning (LEAP) system. Technical report, Stockholm Environment Institute, Stockholm.

Henning, H.-M. and A. Palzer (2014). A comprehensive model for the German electricity and heat sector in a future energy system with a dominant contribution from renewable energy technologies—Part I: Methodology. *Renewable and Sustainable Energy Reviews 30*, 1003–1018.

Herring, S. C., N. Christidis, A. Hoell, M. P. Hoerling, and P. A. Stott (2019). Explaining extreme events of 2017 from a climate perspective. *Bulletin of the American Meteorological Society 100*(1), 1–117.

Hidalgo González, I., S. Quoilin, and A. Zucker (2014). Dispa-SET 2.0: Unit commitment and power dispatch model. Technical report, European Commission.

Hintermann, B. (2016). Pass-through of CO_2 emission costs to hourly electricity prices in Germany. *Journal of the Association of Environmental and Resource Economists 3*(4), 857–891.

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

Hirth, L. (2016). The European electricity market model EMMA – Model documentation. Technical report, Neon Energie, Berlin.

Hirth, L. and F. Ueckerdt (2013). Redistribution effects of energy and climate policy: The electricity market. *Energy Policy 62*, 934–947.

Hoel, M. and K. Schneider (1997). Incentives to participate in an international environmental agreement. *Environmental & Resource Economics 9*(2), 153–170.

Hogan, M. (2017). Follow the missing money: Ensuring reliability at least cost to consumers in the transition to a low-carbon power system. *The Electricity Journal 30*(1), 55–61.

Howells, M., H. Rogner, N. Strachan, C. Heaps, H. Huntington, S. Kypreos, A. Hughes, S. Silveira, J. DeCarolis, M. Bazillian, et al. (2011). OSeMOSYS: The open source energy modeling system: An introduction to its ethos, structure and development. *Energy Policy 39*(10), 5850–5870.

Huber, M. (2017). *Flexibility in power systems - Requirements, modeling, and evaluation.* Ph. D. thesis, Technical University of Munich, Munich.

Huber, M., D. Dimkova, and T. Hamacher (2014). Integration of wind and solar power in Europe: Assessment of flexibility requirements. *Energy 69*, 236–246.

Huber, M., J. Dorfner, and T. Hamacher (2012). Electricity system optimization in the EUMENA region. Technical report, Dii GmbH.

Huber, M. and C. Weissbart (2015). On the optimal mix of wind and solar generation in the future Chinese power system. *Energy 90*, 235–243.

Huld, T., M. Šúri, and E. D. Dunlop (2008). Comparison of potential solar electricity output from fixed-inclined and two-axis tracking photovoltaic modules in Europe. *Progress in Photovoltaics: Research and Applications 16*(1), 47–59.

Huntington, H. G. (2011a). Energy efficiency and climate change mitigation. *Energy Modeling Forum Report 25*(1).

Huntington, H. G. (2011b). The policy implications of energy-efficiency cost curves. *The Energy Journal 32*(1), 7–21.

Huntington, H. G., J. B. Barrios, and V. Arora (2017). Review of key international demand elasticities for major industrializing economies. *U.S. Energy Information Administration working paper 12-2017*.

Huppmann, D. and J. Egerer (2015). National-strategic investment in European power transmission capacity. *European Journal of Operational Research 247*(1), 191–203.

Huppmann, D. and R. Egging (2014). Market power, fuel substitution and infrastructure – A large-scale equilibrium model of global energy markets. *Energy 75*, 483 – 500.

IAEA (2016). Modelling nuclear energy systems with MESSAGE: A user's guide. Technical Report NG-T-5.2, International Atomic Energy Agency (IAEA), Vienna.

IEA (2012). Energy prices and taxes 2012. Technical report, International Energy Agency (IEA), Paris.

IEA (2013). World energy outlook 2013. Technical report, International Energy Agency (IEA), Paris.

IEA (2017a). CO_2 emissions statistics. *URL: https://www.iea.org/statistics/co2emissions/ (accessed: February 2, 2019)*.

IEA (2017b). Energy efficiency 2017. Technical report, International Energy Agency (IEA), Paris.

IEA (2018). CO_2 emissions from fuel combustion. Technical report, International Energy Agency (IEA), Paris.

IEA (2018). Energy efficiency 2018: Analysis and outlooks to 2040. Technical report, International Energy Agency (IEA), Paris.

IER (2013). E2M2s: European Electricity Market Model (stochastic). Technical report, University of Stuttgart, Institute of Energy Economics and Rational Energy Use (IER), Stuttgart.

IRENA (2016). The power to change: Solar and wind cost reduction potential to 2025. Technical report, International Renewable Energy Agency (IRENA), Abu Dhabi.

Jaffe, A. B. and R. N. Stavins (1994). The energy-efficiency gap: What does it mean? *Energy Policy 22*(10), 804–810.

Jamasb, T. and M. Pollitt (2005). Electricity market reform in the European Union: Review of progress toward liberalization & integration. *The Energy Journal 26*, 11–41.

Jamil, F. and E. Ahmad (2011). Income and price elasticities of electricity demand: Aggregate and sector-wise analyses. *Energy Policy 39*(9), 5519–5527.

Jebaraj, S. and S. Iniyan (2006). A review of energy models. *Renewable and Sustainable Energy Reviews 10*(4), 281–311.

Jenkins, J., T. Nordhaus, and M. Shellenberger (2011). Energy emergence: Rebound and backfire as emergent phenomena. *Breakthrough Institute*.

Jevons, W. S. (1865). *The coal question: An inquiry concerning the progress of the nation, and the probable exhaustion of our coal-mines*. London: Macmillan.

Jonghe, C. d., B. F. Hobbs, and R. Belmans (2011). Integrating short-term demand response into long-term investment planning. *Cambridge Working Paper in Economics 1132*.

Joskow, P. L. (2011). Comparing the costs of intermittent and dispatchable electricity generating technologies. *American Economic Review 101*(3), 238–241.

Joskow, P. L. (2013). Symposium on 'capacity markets'. *Economics of Energy and Environmental Policy 2*(2), V–VI.

Joskow, P. L. and J. Tirole (2000). Transmission rights and market power on electric power networks. *The Rand Journal of Economics 31*(3), 450–487.

Juruš, P., K. Eben, J. Resler, P. Krč, I. Kasanický, E. Pelikán, M. Brabec, and J. Hošek (2013). Estimating climatological variability of solar energy production. *Solar Energy 98*, 255–264.

Kalogirou, S. A. (Ed.) (2009). *Solar Energy Engineering*. Boston: Academic Press.

Ketter, W. (2014). *Envisioning and enabling sustainable smart markets*. Inaugural Addresses Research in Management Series. Rotterdam: Erasmus Research Institute of Management (ERIM).

Khazzoom, J. D. (1980). Economic implications of mandated efficiency in standards for household appliances. *The Energy journal 1*(4), 21–40.

Kitous, A., P. Criqui, E. Bellevrat, and B. Chateau (2010). Transformation patterns of the worldwide energy system-scenarios for the century with the POLES model. *The Energy Journal 31*(1), 49–82.

Klein, D., G. Luderer, E. Kriegler, J. Strefler, N. Bauer, M. Leimbach, A. Popp, J. P. Dietrich, F. Humpenöder, H. Lotze-Campen, and O. Edenhofer (2014). The value of bioenergy in low stabilization scenarios: An assessment using REMIND-MAgPIE. *Climatic Change 123*(3), 705–718.

Knopf, B., P. Nahmmacher, and E. Schmid (2015). The European renewable energy target for 2030 – An impact assessment of the electricity sector. *Energy Policy 85*, 50–60.

Kost, C., J. N. Mayer, J. Thomsen, N. Hartmann, C. Senkpiel, S. Philipps, S. Nold, S. Lude, N. Saad, and T. Schlegl (2013). Levelized cost of electricity: Renewable energy technologies. Technical report, Fraunhofer Institute for Solar Energy Systems (ISE), Freiburg.

Krekel, C. and A. Zerrahn (2017). Does the presence of wind turbines have negative externalities for people in their surroundings? Evidence from well-being data. *Journal of Environmental Economics and Management 82*, 221–238.

Kunz, F. and A. Zerrahn (2016). Coordinating cross-country congestion management: Evidence from central Europe. *DIW Discussion Papers 1551*.

Labandeira, X., J. M. Labeaga, and X. López-Otero (2017). A meta-analysis on the price elasticity of energy demand. *Energy Policy 102*, 549–568.

Lamont, A. D. (2008). Assessing the long-term system value of intermittent electric generation technologies. *Energy Economics 30*(3), 1208–1231.

Lejano, R. P. and C. A. Davos (1995). Cost allocation of multiagency water resource projects: Game theoretic approaches and case study. *Water Resource Research 31*(5), 1387–1393.

Lemoine, D. (2016). General equilibrium rebound from energy efficiency innovation. *University of Arizona Department of Economics Working Paper 14-02, revised version 2018*.

Lind, A., E. Rosenberg, P. Seljom, K. Espegren, A. Fidje, and K. Lindberg (2013). Analysis of the EU renewable energy directive by a techno-economic optimisation model. *Energy Policy 60*, 364–377.

Littlechild, S. C. and K. G. Vaidya (1976). The propensity to disrupt and the disruption nucleolus of a characteristic function game. *International Journal of Game Theory 5*(2), 151–161.

Lo Schiavo, L., M. Delfanti, E. Fumagalli, and V. Olivieri (2013). Changing the regulation for regulating the change: Innovation-driven regulatory developments for smart grids, smart metering and e-mobility in Italy. *Energy Policy 57*, 506–517.

Lohwasser, R. and R. Madlener (2009). Simulation of the European electricity market and CCS development with the HECTOR model. *FCN Working Paper 6/2009*.

Loulou, R., U. Remme, A. Kanudia, A. Lehtila, and G. Goldstein (2005). Documentation for the TIMES Model, PART I: Energy Technology Systems Analysis Programme. Technical report, International Energy Agency (IEA), Paris.

Lovins, A. B. (1988). Energy saving resulting from the adoption of more efficient appliances: Another view. *The Energy Journal 9*(2), 155–162.

Lozano, S., P. Moreno, B. Adenso-Díaz, and E. Algaba (2013). Cooperative game theory approach to allocating benefits of horizontal cooperation. *European Journal of Operational Research 229*(2), 444–452.

Lund, H. (2015). EnergyPLAN - Advanced energy systems analysis computer model: Documentation v.13.1. Technical report, Aalborg University, Sustainable Energy Planning Research Group, Aalborg.

Lunde, P. J. (1980). *Solar thermal engineering: Space heating and hot water systems.* New York: Wiley.

Mahmud, K. and G. E. Town (2016). A review of computer tools for modeling electric vehicle energy requirements and their impact on power distribution networks. *Applied Energy 172*, 337 – 359.

Mantzos, L. and P. Capros (1998). The PRIMES version 2 energy system model: Design and features. Technical report, National Technical University of Athens, Athens.

Marcel Šúri, Thomas A. Huld, Ewan D. Dunlop, and Heinz A. Ossenbrink (2007). Potential of solar electricity generation in the European Union member states and candidate countries. *Solar Energy 81*(10), 1295–1305.

Marin, D. and M. Schnitzer (1998). Economic incentives and international trade. *European Economic Review 42*(3-5), 705–716.

Markewitz, P., W. Kuckshinrichs, D. Martinsen, and J.-F. Hake (1996). IKARUS - A fundamental concept for national GHG-mitigation strategies. *Energy conversion and management 37*(6-8), 777–782.

Maschler, M., B. Peleg, and L. S. Shapley (1979). Geometric properties of the kernel, nucleolus, and related solution concepts. *Mathematics of Operations Research 4*(4), 303–338.

Massol, O. and S. Tchung-Ming (2010). Cooperation among liquefied natural gas suppliers: Is rationalization the sole objective? *Energy Economics 32*(4), 933–947.

Masters, G. M. (2004). *Renewable and efficient electric power systems.* Hoboken, NJ: Wiley.

Mattmann, M., I. Logar, and R. Brouwer (2016a). Hydropower externalities: A meta-analysis. *Energy Economics 57*, 66–77.

Mattmann, M., I. Logar, and R. Brouwer (2016b). Wind power externalities: A meta-analysis. *Ecological Economics 127*, 23–36.

Meinshausen, M., N. Meinshausen, W. Hare, S. C. Raper, K. Frieler, R. Knutti, D. J. Frame, and M. R. Allen (2009). Greenhouse-gas emission targets for limiting global warming to 2 C. *Nature 458*(7242), 1158–1163.

Messner, S. and M. Strubegger (1995). User's guide for MESSAGE III. Technical report, International Institute for Applied System Analysis (IIASA), Vienna.

Mickwitz, P. (2003). A framework for evaluating environmental policy instruments. *Evaluation 9*(4), 415–436.

Mideksa, T. K. and S. Kallbekken (2010). The impact of climate change on the electricity market: A review. *Energy Policy 38*(7), 3579–3585.

Mier, M. and C. Weissbart (2018). Power markets in transition: Decarbonization, energy efficiency, and short-term demand response. *ifo Working Paper 284*.

Montgomery, W. (1972). Markets in licenses and efficient pollution control programs. *Journal of Economic Theory 5*(3), 395–418.

Möst, D. and W. Fichtner (2010). Renewable energy sources in European energy supply and interactions with emission trading. *Energy Policy 38*(6), 2898 – 2910.

Möst, D. and D. Keles (2010). A survey of stochastic modelling approaches for liberalised electricity markets. *European Journal of Operational Research 207*(2), 543–556.

Nahmmacher, P., E. Schmid, and B. Knopf (2014). Documentation of LIMES-EU - A long-term electricity system model for Europe. Technical report, Potsdam Institute of Climate Impact Research (PIK), Potsdam.

Nakata, T. (2004). Energy-economic models and the environment. *Progress in Energy and Combustion Science 30*(4), 417 – 475.

NASA (2010). Modern-Era Retrospective analysis for Research and Applications (MERRA). Technical report, National Aeronautics and Space Administration (NASA) Goddard Earth Sciences Data and Information Services Center (GES DISC), Greenbelt.

Nash, J. (1953). Two-person cooperative games. *Econometrica: Journal of the Econometric Society 21*(1), 128–140.

Newbery, D. (2016). Missing money and missing markets: Reliability, capacity auctions and interconnectors. *Energy Policy 94*, 401–410.

Nordhaus, W. (2014). Estimates of the social cost of carbon: Concepts and results from the DICE-2013R model and alternative approaches. *Journal of the Association of Environmental and Resource Economists 1*(1/2), 273–312.

Nylund, H. (2014). Regional cost sharing in expansions of electricity transmission grids. *International Journal of Energy Sector Management 8*(3), 283–300.

Olauson, J. and M. Bergkvist (2015). Modelling the Swedish wind power production using MERRA reanalysis data. *Renewable Energy 76*, 717–725.

Olsthoorn, D., F. Haghighat, and P. A. Mirzaei (2016). Integration of storage and renewable energy into district heating systems: A review of modelling and optimization. *Solar Energy 136*, 49 – 64.

Owen, A. D. (2004). Environmental externalities, market distortions and the economics of renewable energy technologies. *The Energy Journal 25*(3), 127–156.

Paul, A., D. Burtraw, and K. Palmer (2009). Haiku documentation: RFF's electricity market model. Technical report, Resources for the Future (RFF), Washington.

Paulus, M., K. Grave, and D. Lindenberger (2011). A methodology to estimate security of supply in electricity generation: Results for Germany until 2030 given a high level of intermittent electricity feed-in. *EWI Working Papers 2011-10*.

Peleg, B. and P. Sudhölter (2007). *Introduction to the theory of cooperative games*. Berlin and Heidelberg: Springer.

Pfenninger, S., A. Hawkes, and J. Keirstead (2014). Energy systems modeling for twenty-first century energy challenges. *Renewable and Sustainable Energy Reviews 33*, 74–86.

Pfenninger, S., L. Hirth, I. Schlecht, E. Schmid, F. Wiese, T. Brown, C. Davis, M. Gidden, H. Heinrichs, C. Heuberger, S. Hilpert, U. Krien, C. Matke, A. Nebel, R. Morrison, B. Müller, G. Pleßmann, M. Reeg, J. C. Richstein, A. Shivakumaru, I. Staffell, T. Tröndlev, and C. Wingenbach (2018). Opening the black box of energy modelling: Strategies and lessons learned. *Energy Strategy Reviews 19*, 63 – 71.

Pindyck, R. S. (2016). The social cost of carbon revisited. *NBER Working Paper 22807*.

Platts (2013). UDI World Electric Power Plants Data-Base (v. 2013). *(accessed: September 10, 2014)*.

Pryor, S. C. and R. J. Barthelmie (2010). Climate change impacts on wind energy: A review. *Renewable and Sustainable Energy Reviews 14*(1), 430–437.

PSC (2008). Basic concepts in monitoring and evaluation. Technical report, Public Service Commission (PSC), Arcadia.

Ravn, H. F., J. Munksgaard, J. Ramskov, P. Grohnheit, and H. Larsen (2001). Balmorel: A model for analyses of the electricity and CHP markets in the Baltic Sea region. Appendices. Technical report, Elkraft System, Ballerup.

Ray, D. and R. Vohra (2015). Coalition formation. Volume 4 of *Handbook of Game Theory with Economic Applications*, pp. 239–326. Amsterdam: Elsevier.

Richstein, J. C., E. J. Chappin, and L. J. de Vries (2014). Cross-border electricity market effects due to price caps in an emission trading system: An agent-based approach. *Energy Policy 71*, 139 – 158.

Richter, J. (2011). DIMENSION: A dispatch and investment model for European electricity markets. *EWI Working Paper 11/03*.

Ricke, K., L. Drouet, K. Caldeira, and M. Tavoni (2018). Country-level social cost of carbon. *Nature Climate Change 8*, 895–900.

Ridley, B., J. Boland, and P. Lauret (2010). Modelling of diffuse solar fraction with multiple predictors. *Renewable Energy 35*(2), 478–483.

Rienecker, M. M., M. J. Suarez, R. Gelaro, R. Todling, J. Bacmeister, E. Liu, M. G. Bosilovich, S. D. Schubert, L. Takacs, G.-K. Kim, S. Bloom, J. Chen, D. Collins, A. Conaty, A. da Silva, W. Gu, J. Joiner, R. D. Koster, R. Lucchesi, A. Molod, T. Owens, S. Pawson, P. Pegion, C. R. Redder, R. Reichle, F. R. Robertson, A. G. Ruddick, M. Sienkiewicz, and J. Woollen (2011). MERRA: NASA's Modern-Era Retrospective Analysis for Research and Applications. *Journal of Climate 24*(14), 3624–3648.

Roques, F. A. (2008). Market design for generation adequacy: Healing causes rather than symptoms. *Utilities Policy 16*(3), 171–183.

Roth, A. E. and R. E. Verrecchia (1979). The Shapley value as applied to cost allocation: A reinterpretation. *Journal of Accounting Research 17*(1), 295–303.

Rothe, J. and I. Rothe (2015). *Economics and computation: An introduction to algorithmic game theory, computational social choice, and fair division*. Berlin and Heidelberg: Springer.

Rübbelke, D. and S. Vögele (2011). Impacts of climate change on European critical infrastructures: The case of the power sector. *Environmental Science & Policy 14*(1), 53–63.

Samadi, S. (2017). The social costs of electricity generation – Categorising different types of costs and evaluating their respective relevance. *Energies 10*(3), 356.

Savvidis, G., K. Siala, C. Weissbart, L. Schmidt, F. Borggrefe, S. Kumar, K. Pittel, R. Madlener, and K. Hufendiek (2019). The gap between energy policy challenges and model capabilities. *Energy Policy 125*, 503–520.

Schaber, K., F. Steinke, and F. Hamacher (2012). Transmission grid extensions for the integration of variable renewable energies in Europe: Who benefits where? *Energy Policy 43*, 123–135.

Schlachtberger, D. P., T. Brown, S. Schramm, and M. Greiner (2017). The benefits of cooperation in a highly renewable European electricity network. *Energy 134*, 469–481.

Schlecht, I. and H. Weigt (2014). Swissmod – A model of the Swiss electricity market. Technical report, Wirtschaftswissenschaftliches Zentrum (WWZ) der Universität Basel, Basel.

Schlecht, I. and H. Weigt (2015). Linking Europe: The role of the Swiss electricity transmission grid until 2050. *Swiss Journal of Economics and Statistics 151*(2), 125–165.

Schmeidler, D. (1969). The nucleolus of a characteristic function game. *SIAM Journal on applied mathematics 17*(6), 1163–1170.

Schmid, E. and B. Knopf (2015). Quantifying the long-term economic benefits of European electricity system integration. *Energy Policy 87*, 260–269.

Scholz, Y. (2012). *Renewable energy based electricity supply at low costs: Development of the REMix model and application for Europe*. Ph. D. thesis, University of Stuttgart, Stuttgart.

Schröder, A., F. Kunz, J. Meiss, R. Mendelevitch, and C. von Hirschhausen (2013). Current and prospective costs of electricity generation until 2050. *DIW Discussion Papers 68*.

Schröder, A., T. Traber, and C. Kemfert (2013). Market driven power plant investment perspectives in Europe: Climate policy and technology scenarios until 2050 in the model EMELIE-ESY. *Climate Change Economics 04*(supp01), 1340007.

Schulz, A. S. and N. A. Uhan (2013). Approximating the least core value and least core of cooperative games with supermodular costs. *Discrete Optimization 10*(2), 163–180.

Shapley, L. S. (1953). A value for n-person games. *Contributions to the Theory of Games 2*(28), 307–317.

Shukla, P. (1995). Greenhouse gas models and abatement costs for developing nations: A critical assessment. *Energy Policy 23*(8), 677 – 687.

Skar, C., G. Doorman, G. A. Pérez-Valdés, and A. Tomasgard (2016). A multi-horizon stochastic programming model for the European power system. *CenSES Working Paper 2/2016*.

Sorrell, S. (2009). Jevons paradox revisited: The evidence for backfire from improved energy efficiency. *Energy policy 37*(4), 1456–1469.

Steckel, J. C., O. Edenhofer, and M. Jakob (2015). Drivers for the renaissance of coal. *Proceedings of the National Academy of Sciences 112*(29), E3775–E3781.

Steurer, M. (2016). *Analyse von Demand Side Integration im Hinblick auf eine effiziente und umweltfreundliche Energieversorgung.* Ph. D. thesis, University of Stuttgart, Stuttgart.

Stoft, S. (2002). *Power system economics: Designing markets for electricity.* Piscataway, NJ and New York: Wiley-IEEE Press.

Strunz, S., E. Gawel, and P. Lehmann (2016). The political economy of renewable energy policies in Germany and the EU. *Utilities Policy 42*, 33–41.

Su, C.-L. and D. Kirschen (2009). Quantifying the effect of demand response on electricity markets. *IEEE Transactions on Power Systems 24*(3), 1199–1207.

Takayama, T. and H. Hashimoto (1984). Spatial and temporal price and allocation modeling: Some extensions. *Socio-Economic Planing Science 18*(4), 227–234.

Takayama, T. and N. Uri (1983). Quadratic programming or linear complementarity programming. *Regional Science and Urban Economics 13*, 455–470.

Taylor, T. N., P. M. Schwarz, and J. E. Cochell (2005). 24/7 hourly response to electricity real-time pricing with up to eight summers of experience. *Journal of Regulatory Economics 27*(3), 235–262.

Teufel, F., M. Miller, M. Genoese, and W. Fichtner (2013). Review of system dynamics models for electricity market simulations. *Working Paper in Production and Energy 2*.

Thrall, R. M. and W. F. Lucas (1963). N–person games in partition function form. *Naval Research Logistics 10*(1), 281–298.

Tijs, S. H. and T. S. H. Driessen (1986). Game theory and cost allocation problems. *Management science 32*(8), 1015–1028.

Timmerman, J., C. Deckmyn, L. Vandevelde, and G. Van Eetvelde (2013). Techno-economic energy model for low carbon business parks. *Chemical Engineering Transactions 35*, 571–576.

Tol, R. S. (2011). The social cost of carbon. *Annual Review of Resource Economics 3*(1), 419–443.

Trutnevyte, E. (2016). Does cost optimization approximate the real-world energy transition? *Energy 106*, 182–193.

Urban, F., R. Benders, and H. Moll (2007). Modelling energy systems for developing countries. *Energy Policy 35*(6), 3473 – 3482.

van Beeck, N. (1999). Classification of energy models. Technical report, Tilburg University FEW Research Memorandum 777, Tilburg.

van den Bijgaart, I., R. Gerlagh, and M. Liski (2016). A simple formula for the social cost of carbon. *Journal of Environmental Economics and Management 77*, 75–94.

Vangkilde-Pedersen, T., K. L. Anthonsen, N. Smith, K. Kirk, F. Neele, B. van der Meer, Y. Le Gallo, D. Bossie-Codreanu, A. Wojcicki, Y.-M. Le Nindre, C. Hendriks, F. Dalhoff, and N. Peter Christensen (2009). Assessing European capacity for geological storage of carbon dioxide – The EU GeoCapacity project. *Energy Procedia 1*, 2663–2670.

Ventosa, M., A. Baıllo, A. Ramos, and M. Rivier (2005). Electricity market modeling trends. *Energy Policy 33*(7), 897–913.

von Neumann, J., O. Morgenstern, H. W. Kuhn, and A. Rubinstein (1944). *Theory of Games and Economic Behavior*. Princeton: Princeton University Press.

Wang, Z., B. Han, and M. Lu (2016). Measurement of energy rebound effect in households: Evidence from residential electricity consumption in Beijing, China. *Renewable and Sustainable Energy Reviews 58*, 852–861.

Wei, T. and Y. Liu (2017). Estimation of global rebound effect caused by energy efficiency improvement. *Energy Economics 66*, 27–34.

Weissbart, C. (2019). Decarbonization of power markets under stability and fairness: Do they influence efficiency? *Energy Economics*.

Weissbart, C. and G. Blanford (2019). A framework for modeling the dynamics of power markets – The EU-REGEN model. *ifo Working Paper 307*.

Wind Europe (2017). Wind in power: 2016 European statistics. Technical report, Wind Europe, Brussels.

World Nuclear Association (2014). Country profiles. *URL: http://www.world-nuclear.org/information-library/country-profiles.aspx (accessed: November 29, 2014).*

Young, D., G. Blanford, J. Merrick, V. Niemeyer, S. Rose, F. d. La Chesnaye, R. Bedilion, and T. Wilson (2013). PRISM 2.0: Regional energy and economic model development and initial application: US-REGEN model documentation. Technical report, Electric Power Research Institute (EPRI), Pao Alto.

Young, H. P. (1985). Monotonic solutions of cooperative games. *International Journal of Game Theory 14*(2), 65–72.

Young, H. P., N. Okada, and T. Hashimoto (1979). Cost allocation in water resources development: A case study of Sweden. *IIASA Working Paper 79-77.*

Zerrahn, A. and W.-P. Schill (2015). On the representation of demand-side management in power system models. *Energy 84*, 840–845.

Zerrahn, A. and W.-P. Schill (2017). Long-run power storage requirements for high shares of renewables: A review and a new model. *Renewable and Sustainable Energy Reviews 79*, 1518 – 1534.

Zhou, L. (1991). A weak monotonicity property of the nucleolus. *International Journal of Game Theory 19*(4), 407–411.

Eidesstattliche Versicherung

Ich versichere hiermit eidesstattlich, dass ich die vorliegende Arbeit selbständig und ohne fremde Hilfe verfasst habe. Die aus fremden Quellen direkt oder indirekt übernommenen Gedanken, sowie mir gegebene Anregungen, sind als solche kenntlich gemacht. Die Arbeit wurde bisher keiner anderen Prüfungsbehörde vorgelegt und auch noch nicht veröffentlicht. Sofern ein Teil der Arbeit aus bereits veröffentlichten Papers besteht, habe ich dies ausdrücklich angegeben.

Datum: 19. März 2019

Christoph Weissbart