Strategies for a future European power system with high shares of renewable energy: A model-based analysis focusing on uncertainty

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Summary

The European electricity system is currently facing a major transformation, with renewable energy (RE) technologies being expected to constitute an important part of the future generation mix. In light of the recent debate on the European Union's (EU) energy and climate policy until 2030, this thesis contributes both to the academic and public discourse about RE targets and infrastructure needs, and to the methodological advancement of power system models. In particular, I focus on two major aspects: (i) the efficient representation of the RE's temporal variability in large-scale power system models, and (ii) the explicit consideration of uncertainty in analyzing investment strategies for the future European power system.

In the first part of this thesis, I present the long-term investment model for the European electricity system LIMES-EU. The model constitutes the methodological basis of the thesis; it facilitates the analysis of technically feasible and economically viable investment pathways for individual countries and for Europe on aggregate. LIMES-EU simultaneously optimizes investment and dispatch decisions for generation, storage and transmission technologies in an intertemporal way from 2010 to 2050. Despite the model's long-term focus until 2050, it effectively accounts for the short-term variability of electricity demand and infeed from wind and solar power plants. The fluctuations are reflected by modeling the operation of technologies for a set of representative days. These days are selected with a novel and computational efficient approach that is suitable for input data with a large number of different fluctuating time series (i.e. multiple different RE technologies and/or regions). With the approach that has been developed for this thesis it is possible to reflect the characteristic fluctuations of the input data already with a small number of model days. To enable its applicability for other models, it is based on an established clustering algorithm and transparently documented.

The second part of the thesis provides an in-depth analysis of cost-efficient future investment strategies for the European power system in order to reach the EU's long-term decarbonization targets until 2050. The analysis includes an explicit consideration of uncertainty and comprises both aggregate European and national results. Thereby, the work adds important aspects to the European Commission's official impact assessment on the 2030 policy framework as this impact assessment completely disregards the existence of uncertainties and provides only few results on national level. A major focus of the analysis is on the cost-efficient RE expansion until 2030. Their optimal share in the 2030 generation mix varies considerably across the studied scenarios that account for various uncertainties about future techno-economic developments, for example with regard to fuel prices and investment costs. The national results show a strong difference in optimal RE deployment across countries, which is caused by the unequal distribution of RE sources. A cost-optimal RE expansion would result in large international transmission needs and would make some countries importing a large share of their electricity demand from foreign power plants. In addition to determining cost-efficient investment pathways for different future scenarios, the thesis provides an analysis of investment strategies that help to increase the robustness of the power system, i.e. result in a system that performs reasonably well for a large variety of possible futures. The performance of different systems under short-term shocks is tested in a total of

more than 40,000 model runs. The analysis shows, that despite the benefits of a further integration of the European electricity system, strategies promoting the capability of countries to produce at least 95% of their electricity demand domestically significantly help to increase the robustness of the European power system.

Zusammenfassung

Das europäische Stromsystem befindet sich zurzeit in einer Transformation; es wird erwartet, dass Technologien auf Basis erneuerbarer Energien (EE) einen bedeutenden Anteil am zukünftigen Stromerzeugungsmix ausmachen werden. Vor dem Hintergrund der jüngsten Debatte über die Energie- und Klimapolitik der Europäischen Union (EU) bis 2030, trägt diese Arbeit sowohl zum akademischen und öffentlichen Diskurs über EE-Ziele und Infrastrukturbedarf als auch zur methodischen Weiterentwicklung von Stromsystemmodellen bei. Der Schwerpunkt liegt insbesondere auf zwei Aspekten: (i) der effizienten Abbildung der zeitlichen Variabilität von EE in großskaligen Stromsystemmodellen und (ii) der expliziten Berücksichtigung von Unsicherheit in der Analyse von Investitionsstrategien für das zukünftige europäische Stromsystem.

Im ersten Teil der Arbeit stelle ich das langfristige Investitionsmodell für das europäische Stromsystem LIMES-EU vor. Das Modell bildet die methodische Basis der Arbeit; es ermöglicht die Analyse von technisch machbaren und wirtschaftlich sinnvollen Investitionspfaden für einzelne Länder und Gesamteuropa. LIMES-EU optimiert gleichzeitig Investitions- und Einsatzentscheidungen für Erzeugungs-, Speicher- und Übertragungstechnologien in einem intertemporalen Ansatz von 2010 bis 2050. Trotz des langfristigen Fokus bis 2050 berücksichtigt das Modell auf wirksame Weise die kurzfristige Variabilität der Stromnachfrage und der Produktion aus Wind- und Solarkraftwerken. Die Schwankungen werden durch die Modellierung des Technologieeinsatzes für eine Reihe repräsentativer Tage widergespiegelt. Die Auswahl dieser Tage basiert auf einem neuen und recheneffizienten Ansatz, der für Eingangsdaten mit einer hohen Anzahl an schwankenden Zeitreihen geeignet ist (also mehreren verschiedenen EE-Technologien und/oder Regionen). Mit dem Ansatz, der für diese Arbeit entwickelt wurde, ist es möglich die charakteristischen Schwankungen der Eingangsdaten bereits mit einer kleinen Anzahl von Modelltagen widerzuspiegeln. Um die Anwendbarkeit des Ansatzes für andere Modelle zu ermöglichen, basiert dieser auf einem etablierten Clusteralgorithmus und ist transparent dokumentiert.

Der zweite Teil der Arbeit bietet eine eingehende Analyse von kosteneffizienten zukünftigen Investitionsstrategien für das europäische Stromsystem zur Erreichung der langfristigen EU-Dekarbonisierungsziele bis 2050. Die Analyse beinhaltet eine explizite Berücksichtigung von Unsicherheit und umfasst sowohl gesamteuropäische als auch nationale Ergebnisse. Damit ergänzt die Arbeit die offizielle Folgenabschätzung der Europäischen Kommission zur Rahmenpolitik bis 2030 um wichtige Aspekte, da diese Folgenabschätzung die Existenz von Unsicherheiten völlig unbeachtet lässt und nur wenige Ergebnisse auf nationaler Ebene bietet. Ein wesentlicher Schwerpunkt der Analyse liegt auf dem kosteneffizienten EE-Ausbau bis 2030. Deren optimaler Anteil am Stromerzeugungsmix von 2030 variiert beträchtlich zwischen den untersuchten Szenarien, welche verschiedene Unsicherheiten über zukünftige technisch-wirtschaftliche Entwicklungen, etwa in Bezug auf Brennstoffpreise und Investitionskosten, berücksichtigen. Aufgrund der ungleichen Verteilung von erneuerbaren Energieträgern zeigen die nationalen Ergebnisse starke Unterschiede in der optimalen EE-Nutzung zwischen den Ländern. Ein kostenoptimaler EE-Ausbau würde einen großen Bedarf an internationalen Übertragungskapazitäten zur Folge haben und dazu führen, dass einige Länder einen großen Anteil ihres Strombedarfs von

ausländischen Kraftwerken importieren. Neben der Bestimmung von kosteneffizienten Investitionspfaden für verschiedene zukünftige Szenarien bietet die Arbeit eine Analyse von Investitionsstrategien zur Steigerung der Robustheit des Stromsystems, die also dazu führen, dass das System für eine große Bandbreite möglicher Zukünfte angemessen funktioniert. Die Leistung von verschiedenen Systemen unter kurzfristigen Schocks wird in mehr als 40.000 Modellläufen getestet. Die Analyse zeigt, dass trotz der Vorzüge einer weiteren Integration des europäischen Stromsystems Strategien, die dazu führen, dass Länder in der Lage sind mindestens 95% ihres Strombedarfs im Inland zu produzieren, deutlich dabei helfen die Robustheit des europäischen Stromsystems zu steigern.

Chapter 1

Introduction

1. Introduction

The European electricity system is currently facing a major transformation, with renewable energy (RE) technologies being expected to constitute an important part of the future generation mix (European Commission, 2011a; Knopf et al., 2013). In light of the recent debate on the European Union's (EU) energy and climate policy until 2030, this thesis addresses selected questions with regard to the modeling and analysis of the future European electricity system. In particular, I focus on two major aspects: (i) the efficient representation of the RE's temporal variability in large-scale power system models, and (ii) the explicit consideration of uncertainty in analyzing investment strategies for the future European power system.

The expansion in the use of RE technologies is part of the effort to reduce the EU's greenhouse-gas (GHG) emissions until 2050 by more than 80% compared to 1990 levels. The electricity sector plays a central role in this effort. Based on the EU's low-carbon roadmap (European Commission, 2011b), Figure 1 breaks the emission reduction ambition down to the different sectors: As emission reductions promise to be more cost-efficient in the electricity sector compared to other sectors, the electricity sector has to decarbonize almost completely until 2050 and may even contribute to the decarbonization of other sectors through their electrification, i.e. by replacing current energy inputs with electricity (European Commission, 2011a).

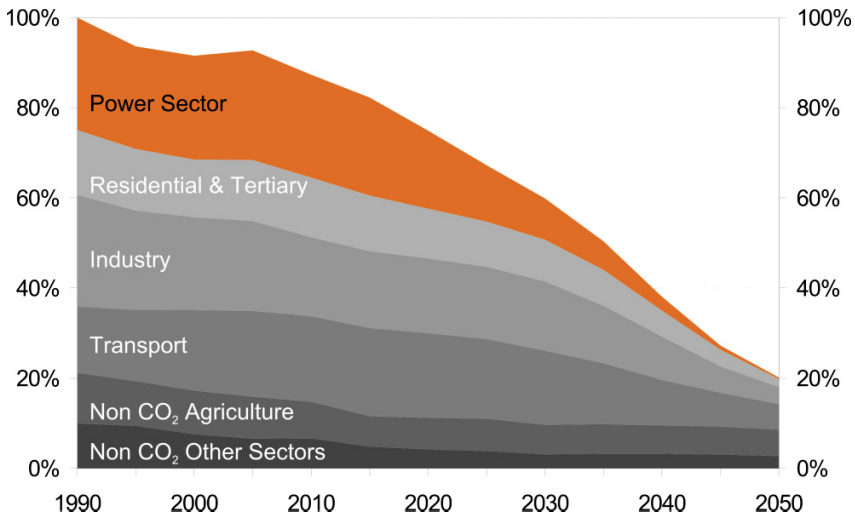

Figure 1: EU27 GHG emissions towards an 80% domestic reduction (100% = 1990). Source: European Commission (2011b)

An increased deployment of RE technologies is not the only option for reducing the electricity sector's carbon emissions. Energy efficiency measures could contribute significantly to the envisioned emission abatements. However, in the long-term a transformation of the electricity sector's supply side is key for reaching an almost complete decarbonization. In this context carbon capture and storage (CCS) and

nuclear power are, so far, the only other low carbon technologies available next to the ones based on RE sources. Though CCS is technically feasible and nuclear power already widely used, the future prospects for an increased deployment of RE technologies are arguably the brightest; not least because it enjoys the widest public support (European Commission, 2012, 2011c).

RE sources suitable for electricity production include wind and solar power, hydropower and bioenergy as well as geothermal and marine energy. While geothermal and marine energy are virtually non-existent in today's electricity mix of the EU, hydropower has been playing a significant role for decades but its growth potential is limited. The share of bioenergy, wind and solar power increased rapidly after the turn of the millennium (EUROSTAT, 2014) and is expected to grow further (Förster et al., 2012; Knopf et al., 2013).

1.1. Challenges arising from an increased deployment of wind and solar power

The expansion in the use of variable renewable energy (VRE) from wind and solar power brings new challenges for the European power system. They are characterized by two important features: their unevenly distributed spatial potential and their temporal variability (IPCC, 2011). Most primary energy carriers can be easily stored and transported before being transformed to electricity where and when needed. This does not apply for kinetic energy from wind and radiant energy from the sun which neither can be stored nor be transported; they directly have to be transformed to electricity, for which there are also only limited storage possibilities.

Figure 2 illustrates the challenges resulting from the VRE's temporal variability by means of the historical hourly time series of electricity consumption and electricity production from wind and solar power in Germany in June and December 2014. The overall VRE share in monthly electricity consumption was fairly similar in both months (18% in June, 20% in December), with solar being more dominant in summer and wind being more dominant in winter (cf. Heide et al., 2010). The hourly share of wind and solar power, however, shows strong variations that do not level out between the two power sources. The infeed from solar power plants naturally shows a strong diurnal pattern caused by the earth's rotation. In contrast, the infeed from wind is much more stochastic. In both summer and winter, the hourly share of VRE in overall electricity consumption varied between 1% and more than 50%. This spread is likely to increase further with additional VRE capacities in the system, demanding for more flexibility of the remaining power system, e.g. in form of higher ramping rates of residual power plants, electricity storage or load shifting (Huber et al., 2014; Kondziella and Bruckner, 2016; Lund et al., 2015).

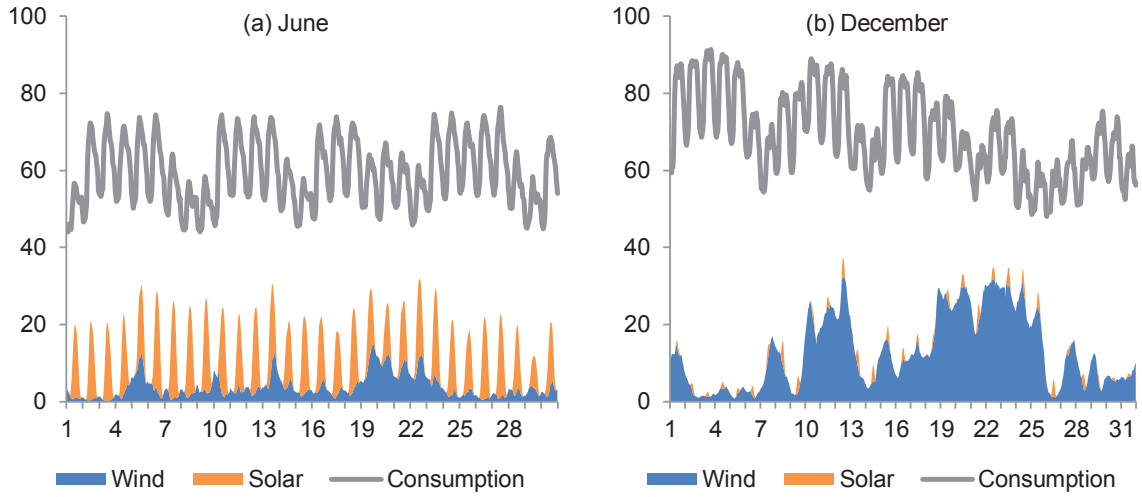

Figure 2: Hourly electricity production from wind and solar power and electricity consumption (all in GW) in Germany in (a) June 2014 and (b) December 2014. Source: Agora Energiewende (2015)

The second important characteristic of wind and solar power is their spatial distribution. Showing the long-term average of wind speeds and solar radiation, Figure 3 illustrates the uneven resource distribution across Europe. While solar radiation is obviously highest in the southern parts of Europe, the highest average onshore wind speeds occur on the British Isles as well as along the coasts of the North Sea and the Baltic Sea. Assuming only limited possibilities for shifting the consumption of electricity closer to those peripheral locations with a high availability of VRE, their rising share in the European generation mix requires either more transmission capacities or the exploitation of comparatively less favorable sites.

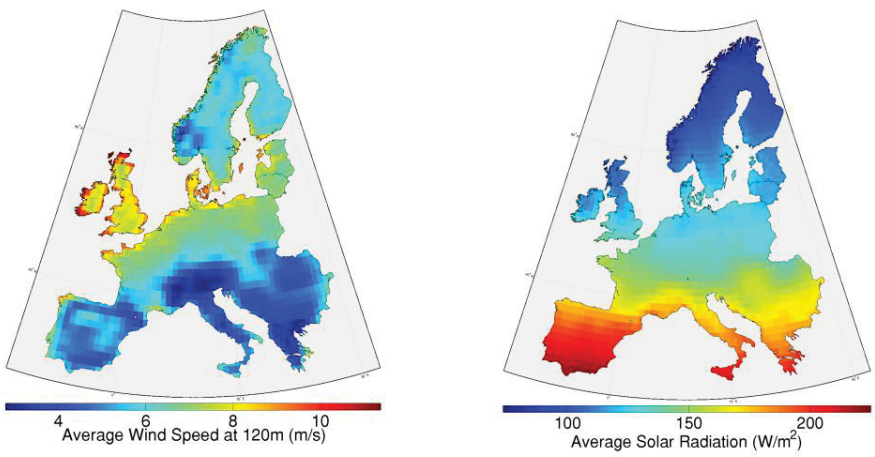

Figure 3: Average onshore wind speed (left) and average annual solar irradiation (right) at different locations in Europe between 1979 and 2011. Source: ECMWF (2012)

1.2. Model-based scientific policy advice for the EU

An established means to analyze the characteristics of a technically feasible and economically viable future European power system is the application of numerical models. There is a large variety of optimization models that determine cost-optimal scenarios for the coming decades. As power systems are characterized by high capital intensity and long-living assets, long-term planning is pivotal. Model-based scenarios therefore play an important role in scientific policy advice, e.g. in the recent discussion about the EU's emission reduction and RE expansion targets for 2030 (European Commission, 2014).

In order to pursue sound policy advice with power system models, these models have to meet a number of requirements which depend on the specific research question at hand. Optimization models that are applied for analyzing cost-optimal investment scenarios until 2030 not only have to account for the EU's medium-term emission reduction targets until 2030 but also for the long-term targets until 2050, i.e. they have to optimize the investment pathway in an intertemporal way. Doing so, the models have to be calibrated to the particularities of the European power system, e.g. reflecting the national characteristics with regard to national resource availability or nuclear power policies. In order to ensure the technical feasibility of scenarios, models have to account for the pivotal technical features of power system assets, e.g. the efficiencies and operational restrictions of thermal power plants. For systems with notable shares of wind and solar power, it is indispensable to appropriately represent their short-term variability. Meeting all these requirements in a model is not trivial as increasing geographical, temporal and technical detail typically protracts the solving time of the algorithm or even makes the model impossible to solve due to computational restrictions.

As models also require input about future expectations, e.g. with regard to future fuel prices and investment costs, it is essential for sound policy advice to explicitly state such assumptions and also to appropriately account for uncertainties in model inputs. Though there are a large number of methods for analyses under uncertainty – such as sensitivity or scenario analysis – the European Commission's impact assessment on the energy and climate policy framework for 2030 does not apply any of them. The most important study for the recent debate on the future European energy policy states the potential impact of different policies for only one single expected future (European Commission, 2014).

1.3. Contribution of this thesis

The modeling and analysis of scenarios for the future European power system with a special focus on the consideration of uncertainties and of the temporal variability of VRE is the major topic of this thesis. It aims to contribute both to the political discussion about the EU's energy policy and to the methodological advancement of long-term power system models. Chapters 2 and 3 focus on the description of a calibrated investment model for the European power system and on questions about modeling power systems with high shares of RE. Chapters 4 and 5 present a detailed analysis of scenarios on the European power system of the year 2030 with an emphasis on the consideration of uncertainty. More specifically, the two parts contribute to the following research questions:

Modeling a future European power system with high shares of RE:

- *What are the relevant characteristics of the European power system that have to be reflected in a numerical model in order to generate technically feasible and economically viable scenarios on future investment pathways and generation mixes both for Europe on aggregate and on national level?*
- *How to implement these characteristics in a computationally efficient way? In particular, how to account for the short-term variability of wind and solar power in long-term power system models? If dispatch is optimized for a set of representative model days, how to select these days from historical data in order to cover the variability of electricity demand and wind and solar power in an efficient way?*

Analysis of the 2030 power system considering uncertainty:

- *What is the cost-optimal RE share in the European electricity mix of the year 2030 that is in compliance with the long-term decarbonization targets until 2050? How dependent is this cost-optimal RE level on specific assumptions about future developments? What are the additional costs of a non-optimal RE target? How are cost-optimal RE investments distributed across European countries?*
- *In contrast to a cost-optimal system for a deterministic future, what does a robust European power system look like, i.e. a system that also performs well under unexpected short-term shocks? How to draw robust solutions from an optimization model?*

The work with regard to these research questions is based on the development of LIMES-EU, the Long-term Investment Model for the Electricity System of EUrope, which is an advancement of earlier versions of the LIMES modeling framework developed at the Potsdam Institute for Climate Impact Research (Haller et al., 2012; Ludig et al., 2015, 2011; Schmid and Knopf, 2015). The model simultaneously determines cost-minimizing investment and dispatch decisions for generation, storage and transmission technologies that are needed to serve future electricity demand and to comply with future energy and climate policies. This integrated approach together with an intertemporal optimization until 2050 allows analyzing consistent and cost-efficient pathways for the future development of the European power system – both on aggregate and on national level.

The remainder of this introductory chapter is structured along the two major topics of this thesis: Modeling power systems with high shares of RE and the consideration of uncertainty in the analysis of scenarios for the future European power system. Section 2 gives an introduction to the work presented in Chapters 2 and 3, namely the modeling of a future European power system with high shares of RE. Section 3 focuses on the work presented in Chapters 4 and 5, namely the analysis of scenarios on the future European power system of the year 2030 with an emphasis on the consideration of uncertainty. Section 4 concludes the introductory chapter with an outline of the thesis and its main results.

2. Modeling a future European power system with high shares of RE

Questions concerning technologically feasible and economically viable investment pathways – such as the research questions above – are typically answered with the help of numerical models. They play an important part in scientific policy advice. In the EU, the PRIMES model is arguably the most influential one: All major proposals of the European Commission concerning medium- and long-term energy policies are backed by an impact assessment based of the PRIMES model (European Commission, 2014, 2011a, 2011d). PRIMES is a multi-market equilibrium model for the European energy system, comprising electricity, gas and other fuel markets (E3MLab, 2014). The power supply module is designed as an optimization model that minimizes total costs of electricity provision for an exogenous demand; it optimizes both the future capacity and generation mix. Optimization approaches are very common in long-term energy system modeling. The optimization models TIMES (Loulou et al., 2005) and MESSAGE (IIASA, 2001) have been applied to energy systems all over the world and have played an important part in several policy decisions (Chiodi et al., 2015; Connolly et al., 2010). Next to these energy system models, that explicitly cover power, heat, transport and industrial sectors, there is a large variety of models focusing exclusively on the power system which enables a larger scope or detail with regard to the covered time span, technologies and regions.

The large set of power system investment optimization models can be separated into two groups, depending on whether investment decisions are optimized for a single moment in time (e.g. REMIX (Scholz, 2012), EMMA (Hirth, 2013), URBS-EU (Schaber et al., 2012), BALMOREL (Ravn, 2001), ReEDS (Short et al., 2011)) or for several time steps simultaneously (e.g. OSeMOSYS (Howells et al., 2011), DIMENSION (Richter, 2011), THEA (Nicolosi, 2011a), SWITCH (Fripp, 2012), LIMES (Haller et al., 2012)). The former models typically optimize investments for a steady state, i.e. under the assumption that the future techno-economic and political parameters do not change. A cost-optimal investment pathway considering an evolving economic and political environment can only be determined by intertemporal models.[1]

The focus of this thesis is on the year 2030. As this year constitutes an intermediate state on the way towards an almost complete decarbonization of the European power system until 2050 (European Commission, 2011b), the ability to account for a time-variant policy framework is a prerequisite for the analyses pursued here. I therefore base my work on the LIMES modeling framework, which provides an intertemporal optimization approach spanning from 2010 until 2050.

The benefits of an intertemporal optimization come at the costs of higher computational demand. The simultaneous optimization of investments for multiple time steps results in restrictions with regard to the representation of technical details and with regard to the temporal resolution of dispatch optimization. Adequately modeling the European power system therefore includes deliberate decisions about the representation of certain power system characteristics as well as the development of

[1] Recursive dynamic approaches (as applied in the ReEDS model (Short et al., 2011)) with sequential solving of single time steps can allow for an approximation of intertemporal solutions, though.

advanced methods for a more computational efficient representation. A transparent model documentation and validation is vital in this context.

The following section (2.1) briefly presents the model LIMES-EU which is described in more detail in Chapter 2. The model that is based on the LIMES modeling framework was developed for this thesis and is applied to generate cost-optimal scenarios for the European power system. Section 2.2 focuses on a novel approach developed for the model in order to adequately reflect the temporal variability of demand, wind power and solar power in a computational efficient way. This temporal variability increases the required flexibility of the remaining power system and is therefore a decisive factor in power system models. Chapter 3 describes the approach in more detail.

2.1. The long-term investment model LIMES-EU

LIMES is a linear optimization[2] modeling framework that simultaneously determines cost-minimizing investment and dispatch decisions for generation, storage and transmission technologies that are needed in order to serve an exogenous future demand for electricity and to comply with future energy and climate policies. Its integrated approach together with an intertemporal optimization until 2050 allows for analyzing consistent and cost-efficient pathways for the future development of a power system – both on aggregate and on regional level. The LIMES modeling framework has been applied in numerous peer-reviewed studies on the German (Ludig et al., 2015, 2011) and European power system (Schmid and Knopf, 2015) as well as on an integrated system comprising Europe and the MENA[3] region (Haller et al., 2012).

In order to answer the research questions raised in Section 1.3, I developed the model version LIMES-EU which includes updated and revised input data, new model equations, a revision of the geographical scope and resolution as well as a better representation of the temporal variability of wind and solar power. LIMES-EU comprises 26 of the 28 EU Member States[4] plus Switzerland, Norway and the Balkan region. Except for the Balkan region, all countries are represented as individual model regions in order to analyze both national and aggregate European results. The model is calibrated to the base year 2010, for which installed power generation and storage capacities are fixed according to Platts (2011) and EUROSTAT (2013); transmission capacities are based on ENTSO-E (2013).

In order to accommodate both long-term investment decisions and short-term fluctuations of wind, solar irradiance and demand, LIMES-EU makes use of two different time scales. The long-term scale ranges from 2010 to 2050 and is subdivided in *time steps* of five or ten years. Investment decisions are optimized for each time step. The short-term scale subdivides the time steps into multiple *time slices*. Eight time slices – with a length of three hours each – add up to one representative day. A weighting factor is given to each representative day; together they add up to one model year. Assigning different weights to representative days allows for incorporating both days with common and rare load patterns. The balancing of electricity demand and supply, i.e. the operation of generation, storage and

[2] The model is formulated in GAMS and uses the linear solver CPLEX. http://www.gams.com
[3] Middle East & North Africa
[4] excluding Malta and Cyprus

transmission capacities, is modeled for each time slice. A major novelty in LIMES-EU is the way how these time slices are selected from historical data; the approach developed for this thesis is presented shortly in the following section (2.2) and in more detail in Chapter 3. The next paragraphs focus on the representation of generation, transmission and storage technologies in the model.

Generation technologies: There are 14 different generation technologies modeled in LIMES-EU. The VRE technologies wind onshore, wind offshore, solar photovoltaic (PV) and concentrated solar power (CSP) are intermittent with their availability varying both on a spatial and temporal scale. To account for intra-regional differences in wind and solar resources, each model region is subdivided into three resource grades per intermittent generation technology. Dispatchable technologies in LIMES-EU comprise lignite and hard coal power plants, natural gas combined cycle power plants and gas turbines as well as nuclear, biomass and hydro power plants. Electricity generation based on lignite, hard coal and natural gas is associated with CO_2 emissions. Optionally, those power plants can be enhanced with CCS technology that reduces their CO_2 emissions by storing them underground.

Transmission technologies: Transmission is modeled as a transport problem from the center of one region to the center of a neighboring region – with the maximum transmissible amount of electricity being restricted by the installed net transfer capacity (NTC). The transmission of electricity between model regions is associated with losses. Network constraints and transmission losses within a region are not explicitly modeled in LIMES-EU ('copperplate' assumption).

Storage technologies: Two generic storage technologies are available in LIMES-EU: intraday and interday storage. While intraday storages can only shift electricity provision between time slices of the same day, interday storages are able to shift electricity provision between all time slices of the same year. Compared to intraday storage, interday storage is subject to higher investment costs and higher storage losses.

A detailed documentation of the model together with a list of all model equations and the relevant input data are given in Chapter 2.

2.2. Accounting for the temporal variability of VRE in power system models

As described above, LIMES-EU (and most other intertemporal power system models) optimizes the operation of generation, storage and transmission technologies only for a limited number of representative situations within the year, the so-called time slices. However, it is not obvious which time slices should be selected from historical data and how to decide whether the selection is appropriate. This is especially the case for models with multiple fluctuating time series and multiple regions. In order to aggregate the time series data into representative time slices, a structured and reproducible algorithm is needed. Up until now, the selection of days has been based largely on heuristics and is rarely documented in detail in the description of power system models.

Before VRE technologies were introduced into power systems, fluctuations in demand were the major drivers of variability in the system. Hence, the traditional method for developing time slices is based purely on demand fluctuation, e. g. between day and night, between working-days and week-ends and

between different seasons (e.g. Fürsch et al., 2011; Pina et al., 2011; Short et al., 2011). With the rise of wind and solar power an adequate representation of their fluctuating temporal availability in the model's time slices becomes more important; ignoring this fundamental characteristic could result in biased model results (Kannan and Turton, 2012; Nicolosi, 2011b). Consequently, a number of alternative time slice approaches have been developed that go beyond the demand-based approach in order to better account for the fluctuations of VRE (e.g. Golling, 2012; Poncelet et al., 2015; Sisternes and Webster, 2013). Despite the variety of new time slice approaches, all approaches to date are subject to certain shortcomings: They are either based on only one VRE time series, they are focused on only one region or disregard different spatial compositions of feed-in levels, or they lead to a number of time slices that is too large for long-term intertemporal investment models. In addition, only few provide a distinct validation of their approach.

Chapter 3 presents a novel approach for selecting representative time slices for long-term power system models in an automated and reproducible way. It is applied on historical electricity demand and weather data to group together days with similar diurnal patterns of demand and VRE infeed. Each group of similar days is then used to define an individual representative day in the power system model LIMES-EU. Unlike most existing approaches, this one is suitable for input data with a large number of different fluctuating time series, i.e. multiple different VRE technologies and/or multiple regions. Due to its generic design based on Ward's (1963) hierarchical clustering algorithm, it is readily applicable to other power system models.

An analysis with LIMES-EU shows that already six representative days (48 time slices) are sufficient to reflect the major characteristics of the fluctuating time series and to achieve reliable model results. The use of fewer representative days would lead to distorted model results in form of an underestimation of overall system costs and higher VRE shares deemed cost-optimal by LIMES-EU.

3. Analysis of the 2030 power system considering uncertainty

A sound representation of technology characteristics and a proper calibration to the model's focus region are key to model scenarios on the future of a power system. With the configuration described above, LIMES-EU is well suited to generate cost-optimal future scenarios on the European power system. When analyzing such scenarios about the future, e.g. with regard to the European energy policy for 2030, it is important to consider the presence of uncertainty. Deviations from the expected future development of external parameters such as fuel prices and investment costs may alter the cost-optimal configuration of a power system significantly. This aspect is often neglected in policy relevant scenario studies: The most important model-based study on the recent debate about the EU's energy policy targets until 2030 completely disregards the possibility of deviations from the expected future (European Commission, 2014). Though the study includes multiple different policy scenarios, it considers only one single scenario of techno-economic developments. Starting from this gap in recent policy advice, Chapters 4 and 5 are focused on research questions with an explicit emphasis on future uncertainties.

There is a large variety of tools to account for incomplete knowledge about the future in energy sector investment decisions, system planning and policy making (cf. Andrews, 1995; Hickey et al., 2010; Zeng et al., 2011). The applicability of individual approaches depends on the level of knowledge about the future, i.e. whether there is risk, uncertainty or ignorance. In case of risk both the possibility and the probability of future states are known; under uncertainty – sometimes also termed “deep uncertainty” – only the possibility is known; and ignorance exists when even the possibility of events is unknown (cf. Stirling, 1994). Stirling (1994) points out that we are not able to anticipate every possible contingency and outcome affecting the electricity sector, and it is thus ignorance that dominates real electricity investment decisions. However, the assumption of ignorance would preclude any numerical analysis of possible futures which could provide meaningful insights. For the analyses in Chapters 4 and 5, I therefore assume the existence of uncertainty: the possibility of certain futures is known, but not their probability.

An established method for analyzing different possible futures without the necessity to assign probabilities is scenario analysis. In Chapter 4, I apply scenario analysis to examine research questions with regard to the optimal RE share and a corresponding RE target for the European power generation mix of 2030. In Chapter 5, I adopt the framework of Robust Decision Making (Lempert et al., 2006) in order to determine the characteristics of a European power system that is not necessarily cost-minimal for the expected future, but promises a robust performance for a large variety of possible futures, in particular with regard to the possibility of short-term shocks. The analyses pursued in the two chapters are described shortly in the following two subsections.

3.1. The European RE target for 2030

The strong expansion of RE technologies in the European electricity sector during the last decade has been accompanied by national and EU-wide expansion targets and resulting support mechanisms. On EU level, the European Council agreed in 2007 for the first time on an explicit target for the share of RE in the provision of final energy consumption (European Council, 2007). This was put into legislation within the context of the “EU climate and energy package” for the target year 2020 (the so-called 20-20-20 package). In order to provide a stable and reliable planning environment, the European Council recently decided on the climate and energy policy framework for 2030: In October 2014, the Council set the targets of at least 40% for domestic GHG reduction and at least 27% for the RE share in final energy consumption (European Council, 2014).

As many other decisions on the EU’s climate and energy policy before, the decisions on the climate and energy policy framework for 2030 are backed by an impact assessment based of the PRIMES model (European Commission, 2014). According to this impact assessment, the 27% RE target is cost-optimal with regard to a 40% GHG reduction until 2030 and the long-term decarbonization target until 2050. For the electricity sector, the economy-wide 27%-target translates to an electricity generation share of 49% in 2030 (European Commission, 2014). The considerably higher sectoral share underlines the importance of the electricity sector in delivering the overall RE target.

Chapter 4 complements the analysis pursued in the impact assessment with a more detailed analysis for the electricity sector. Besides adding to the PRIMES-based findings more detailed information on the electricity sector, the aim of the chapter is to overcome an important weakness of the PRIMES scenarios: They completely disregard the existence of uncertainty. The impact assessment presents several scenarios with varying policies, but techno-economic assumptions such as future investment costs and fuel prices are not subject to scenario variations. As it is highly uncertain if these assumptions hold, I study the cost-optimal share of RE in the European electricity mix of the year 2030 under a variety of possible futures and also estimate the costs of a RE target that is set higher than the cost-optimal one.

The analyzed scenarios cover variations in investment costs for VRE and storage technologies, fuel costs for biomass, nuclear power and CCS policies as well as energy efficiency and transmission expansion. It turns out that the optimal RE share in 2030 varies significantly across the considered scenarios, namely between 43% and 56%. The 49% share determined by PRIMES is well within this uncertainty range. However, given these large uncertainties, it is possible that a future target for the electricity sector is set higher than the cost-optimal share. The analyses in Chapter 4 suggest that such a target would lead to large additional investment costs before 2030, but these additional costs would level out in the long-term due to savings in fuel consumption: Depending on the actual level of the target, its long-term costs are likely to stay below 1% of total discounted system costs over the period 2011–2050.

In addition to the aggregated European results, the LIMES-EU model also allows for analyzing future scenarios on country-level. Caused by the uneven distribution of solar and wind resources discussed in Section 1.1, the analyses pursued in Chapter 4 show that the cost-optimal RE share in 2030 varies considerably across countries: In the default scenario, the national shares vary between 15% (Czech Republic) and nearly 100% (Norway). The different levels of investments in RE capacities have strong implications for the electricity trade balance of the countries. Compared to today, the scenarios show a significant intensification of cross-border electricity trade, with some countries importing a large share of their annual electricity consumption from abroad.

3.2. Strategies for a robust European power system

The detailed analysis of the European electricity sector with an explicit consideration of future uncertainties as presented in the previous section (and in more detail in Chapter 4) provides a significant additional value to the official PRIMES-based impact assessment. Despite scenario analysis being an established method in case of uncertainty, it has an important shortcoming though: The future power systems resulting from the model are cost-optimal for the given scenario assumptions, but there is no information on how these respective systems would perform under a future that is different from the expected scenario. The optimization is done under the assumption of a deterministic future. The work pursued in Chapter 5 starts from this shortcoming of classic scenario analysis and aims at generating investment pathways with LIMES-EU that result in a robust power system.

Electricity systems are constantly exposed to geopolitical, techno-economic and natural uncertainties. It is therefore crucial to design the system in a way that it performs well under a variety of possible futures

– not only the one that is perceived as the most likely. In this context, sudden short-term shocks that do not allow for an adaptation of the capacity stock are particularly challenging. Policy making based on studies that disregard the possibility of shocks may lead to serious vulnerabilities of the electricity system and – given the various uncertainties about the future – may actually not be as cost-efficient as the studies suggest.

So what are viable strategies, beyond pure cost-minimization, for ensuring that an envisioned power system also performs well under shocks? To answer this question, I focus on the concept of robustness, which can more generally be defined as a reduced sensitivity of output to shocks (Anderies et al., 2013). Reaching robustness implies diverging from the strategy that would be optimal in case of absolute certainty, and instead engaging in a strategy that yields near-optimal outcomes for a large variety of possible futures (Rosenhead et al., 1972). In order to determine which strategies are viable to increase the robustness of the European power system against shocks, the classic optimization approach of power system planning is combined with the tools of Robust Decision Making (Lempert et al., 2006).

Chapter 5 provides an analysis on how a cost-minimal European power system that is determined by LIMES-EU performs under shocks and compares this performance with systems based on different design strategies other than pure cost-minimization, namely increased fuel diversity, self-sufficiency and redundancy as well as excess transmission and storage expansion. The assessment of the different strategies is based on an exceptionally high number of 40,192 model runs with LIMES-EU. The analysis focuses on large-scale shocks that could possibly affect the entire European power system and cover shocks on both thermal and RE-based power generation, on the transmission system as well as on the fuel supply.

Of all strategies tested, additional national generation capacities are most viable to reduce the loss of load in case of shocks. The resulting system is not cost-optimal for the expected future without shocks; but the additional costs for a robust system in 2030 (about 0.1% of total system costs until 2030) are low compared to the benefits of significantly increasing the power system's robustness. At first sight, the viability of a national strategy contradicts the findings of Chapter 4 that stressed the benefits of an interconnected European power system with some countries importing significant amounts of electricity to serve their domestic demand. However, the effect of the robust strategy is largely limited to the capacity mix and the *capability* to generate electricity domestically if in need. In case no shock occurs, the overall generation mix as well as the international trade patterns are very similar to the default run of pure cost-minimization and the results presented Chapter 4.

4. Outline of the thesis and main results

The work presented in Sections 2 and 3 of this introductory chapter is the subject of four individual scientific articles that are included in this cumulative thesis as Chapters 2 to 5. The structure of the thesis is visualized in Figure 4 and outlined in more detail in the following.

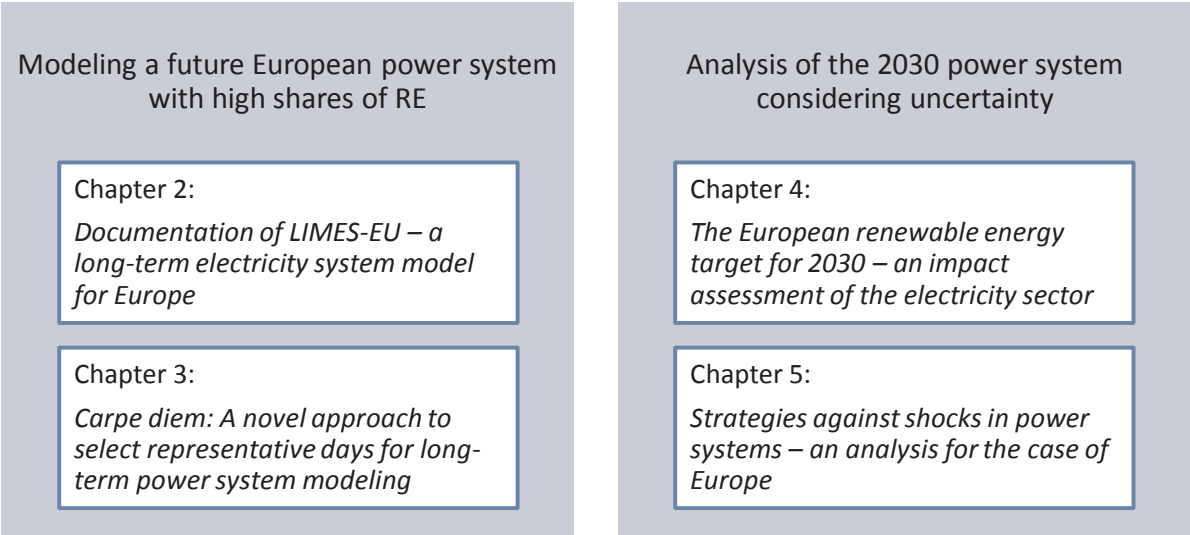

Figure 4: Overview of the structure of the thesis. Source: own visualization.

Chapters 2 and 3 focus on the modeling of a future European power system with high shares of RE. Chapter 2 provides a transparent documentation of the long-term European power system model LIMES-EU including its model equations and input data. The model version, which is based on the LIMES modeling framework, was developed for this thesis in order to analyze the research questions addressed in Chapters 4 and 5. A major novelty in this model version is the improved representation of the temporal variability of wind and solar power. The underlying method is described in detail in Chapter 3.

The analyses on the European power system of 2030 with an explicit consideration of uncertainty are the subject of Chapters 4 and 5. Chapter 4 analyzes the cost-optimal future European generation mix for a variety of different scenario assumptions. A special focus is put on the role of RE in the future generation mix and the costs of a RE target that is higher than optimal. Next to an aggregate European analysis, the chapter also includes an analysis of the cost-optimal expansion of RE technologies on national level. In contrast to analyzing optimal power systems for different futures, Chapter 5 is concerned with the determination of a robust power system that performs reasonably well for a variety of possible futures. To this end, the chapter analyzes the performance of different future power systems under short-term shocks in a total of more than 40,000 model runs.

The main results of Chapters 2 to 5 can be summarized as follows:

- An insufficient representation of the temporal variability of electricity demand, wind power and solar power leads to biased results with higher VRE shares and an underestimation of total system costs. Appropriately accounting for their characteristic fluctuations is therefore an essential feature of power system models (Chapter 3).
- The approach developed for LIMES-EU allows for effectively covering the fluctuations in the European power system with as few as six representative model days. The approach is readily applicable to many kinds of power system models; it is suitable for input data with a large number of time series for which appropriate approaches were missing so far (Chapter 3).

- With its integrated optimization of generation, storage and transmission capacities in an intertemporal way, the model LIMES-EU is well suited for determining cost-efficient and consistent investment strategies for the future European power system both on national and aggregate European level (Chapter 2).
- The analysis of the cost-optimal European power system of 2030 highlights the importance of considering uncertainty: The optimal RE share that is in line with the long-term decarbonization targets until 2050 is subject to large uncertainties and varies between 43% and 56% across the studied scenarios (Chapter 4).
- Setting a RE target for 2030 that is higher than the cost-optimal share could result in large additional costs until 2030. However, these costs are balanced out by savings in fuel costs in the subsequent years. The long-term costs of a non-optimal target are therefore likely to stay below 1% of the total system costs over the whole period 2011-2050 (Chapter 4).
- The national results for 2030 show a strong difference in optimal RE deployment across countries, which is caused by the unequal distribution of RE sources. A cost-optimal expansion of RE technologies would result in large international transmission needs and would make some countries importing a large share of their electricity demand from foreign power plants (Chapters 4 & 5).
- Despite the benefits of a further integration of the European electricity system, it may be sensible for countries to keep their capability of always producing at least 95% of their electricity demand domestically: This strategy significantly increases the robustness of the power system against shocks (Chapter 5).
- Accounting for the possibility of shocks is vital when deciding on future investment pathways: The strategy of pure cost-minimization for a deterministic future is shown to incorporate large vulnerabilities compared to the robust strategy of national reserve capacities (Chapter 5).

Chapter 6 provides a comprehensive synthesis of the thesis. It summarizes and discusses the results of the previous chapters, reviews the methodological approach of this thesis and concludes by providing options for further research.

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Chapter 2

Documentation of LIMES-EU - A long-term electricity system model for Europe *

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Documentation of LIMES-EU - A long-term electricity system model for Europe

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This paper presents a detailed documentation of LIMES-EU - the Long-term Investment Model for the Electricity Sector of EUrope. LIMES-EU is a linear optimization model that simultaneously optimizes investment and dispatch decisions for generation, storage and transmission technologies. Its integrated approach together with an intertemporal optimization from 2010 to 2050 allows for analyzing comprehensive scenarios on the cost-efficient future development of the European power system. Despite the model's long-term focus until 2050, LIMES-EU effectively accounts for the short-term variability of electricity demand and the renewable energy sources wind and solar. In order to provide transparency, this paper gives a detailed overview of the model's underlying assumptions, its input data and a full list of the model equations.

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Contents

1. Introduction

The Member States of the European Union (EU) have repeatedly stated their will to reduce greenhouse gas emissions in order to contribute to global climate change mitigation (European Council 2007, 2009, 2011). The aspiration to reduce CO_2 emissions until 2050 by 80% compared to 1990 levels translates to huge transformational demand in the energy-related sectors transport, heat and power. According to the European Commission's Low Carbon Roadmap (European Commission 2013a) the power sector has to decarbonize faster and stronger than both the transport and heat sector, reaching 95-99% CO_2 reduction in the year 2050. However, there are still numerous open questions of how to achieve such a strong transformation of the electricity system - comprising technical, economic and political aspects.

The core assets of the power sector - electricity generation, storage and transmission technologies - are characterized by long technical lifetimes that span over several decades. Long-term planning by relevant actors such as policy makers, transmission system operators and electricity producers is therefore pivotal. Within the framework of the '20-20-20' targets the European policy makers implemented specific policies to reach the targets with regard to the reduction of CO_2 emissions, the deployment of renewable energy sources (RES) and the reduction of final energy consumptions until 2020. However, for the time after 2020 dedicated policies are yet undecided, both for reaching the long-term target of 80% emission reductions until 2050 as well as intermediate targets for emission reductions and RES deployment. In order to support policy makers in identifying robust policy targets long-term scenarios are needed to explore possible pathways for the European electricity sector that are technically feasible and economically sensible.

The **L**ong-term **I**nvestment **M**odel for the **E**lectricity **S**ector of **EU**rope LIMES-EU was developed to facilitate a long-term assessment of the European power system on aggregate and national level. Incorporating electricity generation, storage and transmission technologies LIMES-EU simultaneously optimizes investment decisions in 5-year steps from 2010 to 2050 for each country in Europe taking into account European-wide and country-specific climate and energy targets. In this way LIMES-EU delivers consistent and cost-efficient scenarios for the future European power system.

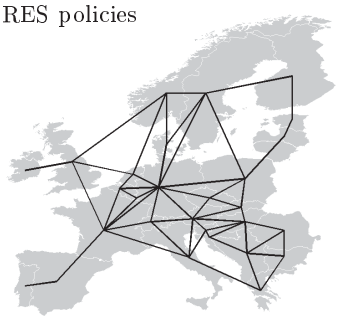
LIMES-EU is especially useful to analyze the integration of variable renewable energy sources (vRES) such as wind and solar into the European power system. Despite its long-term focus it accounts for short-term fluctuations of demand and vRES supply when determining the optimal electricity generation mix. Its comprehensive approach to simultaneously optimize investments in generation and storage technologies as well as cross-border transmission capacities allows for a sound technological and economic analysis of vRES integration options.

This documentation aims to give a comprehensive and detailed description of LIMES-EU. Many of the parameters used in the model depend on future technological, economic and political developments and are therefore highly uncertain. In order to facilitate a correct

LIMES-EU - The **L**ong-term **I**nvestment **M**odel for the **E**lectricity **S**ector of **EU**rope

Type of model
linear optimization model
implemented in GAMS using the CPLEX Solver

Objective of the model
minimizing the cumulated costs of electricity provision
for a given electricity demand and exogenous CO_2/RES policies
by optimizing investment and dispatch decisions
for generation, storage and transmission capacities



Temporal scope & resolution
from 2010 to 2050 in 5-year steps
6 representative days per year
8 time slices per day
perfect foresight

Geographical scope & resolution
Europe; 29 model regions
all Member States of the European Union (without Malta and Cyprus)
plus Norway, Switzerland and an aggregated region of non-EU Balkan countries

Technologies
generation technologies
nuclear, hard coal, lignite, natural gas (combined cycle / gas turbine)
hard coal CCS, lignite CCS, natural gas (combined cycle) CCS
hydro, wind onshore, wind offshore, photovoltaic, concentrated solar power, biomass
storage technologies
intraday, interday
transmission technologies
net transfer capacities between model regions

Figure 1: LIMES-EU in a nutshell

interpretation of our model results and to provide a maximum amount of transparency, we aim to disclose all parameter values used for our default scenarios and describe the assumptions on which our parameter choice is based. A large part of the model equations as well as some calibration data are same to the earlier LIMES-EU$^+$ version of the model. Though they are already discussed in the supplementary material of Haller et al. (2012) they are stated here again for the sake of comprehensiveness.

The following Section gives an overview about the model and its basic functioning. Section 3 briefly presents a novel approach for efficiently decreasing the intra-annual resolution of the model. It allows for keeping computational demand to a minimum while at the same time correctly reflecting the short-term variability of vRES. A more detailed description of the approach is provided in Nahmmacher et al. (2014). Section 4 and 5 discuss the standard parameter assumptions used to run the model, with Section 4 focusing on technology-specific parameters that are same for every model region and Section 5

focusing on region-specific input data. All prices and cost stated in this paper are given in 2010 prices. An overview about different climate and energy-related policies that can be implemented in LIMES-EU is presented in Section 6. Section 7 provides a validation of the model. A comprehensive list of all model equations can be found in Appendix A. Region names are often abbreviated by a two-letter code in this documentation; an explanation of the codes that are based on ISO 3166-1 is given in Appendix B.

2. Model Overview

2.1. Objective Function

The model is formulated as an intertemporal social planner problem with perfect foresight. It minimizes the cumulated discounted costs of electricity provision for all model regions over the whole model time span simultaneously (Equation 1). The total system costs C^{tot} are the intertemporal sum of the costs for capacity investments C_t^I, fuel costs C_t^F, operation and maintenance costs C_t^{OM} as well as possible CO_2 emission costs $C_t^{CO_2}$ of each time step t. The factor Δt accounts for the time span between two model years. A salvage value V for the capacity stock that remains at the end of the time horizon is subtracted. All values are discounted to present values using the discount rate ρ which is set to 5% in the standard case. A comprehensive list of all model equations is given in Appendix A.

$$C^{tot} = \sum_t \left(\Delta t \, e^{-\rho(t-t_0)} \left(C_t^I + C_t^F + C_t^{OM} + C_t^{CO_2} \right) \right) - e^{-\rho(t_{end}-t_0)} \, V \tag{1}$$

The electricity demand is exogenous to the model. The focus is on the supply side of the electricity system and its interactions with the transmission infrastructure. Using a social planner approach, the model abstracts from the nearly infinite amount of heterogeneous players in the electricity sector. The social planner solution is equivalent to the outcome of a decentralized market under perfect market conditions. Thus the model results show how a cost-optimal European electricity system under the given assumptions would look like, not how the European electricity system that faces considerable market distortions will evolve within the next decades.

The model is formulated in GAMS[1] and uses the linear solver CPLEX.

2.2. Geographical Resolution

The current version of LIMES-EU optimizes the electricity system of the EU28 countries[2] plus Switzerland, Norway and the Balkan region. Except for the Balkan region,

[1] General Algebraic Modeling System, http://www.gams.com
[2] excluding Cyprus and Malta

all countries are modeled as individual entities. They differ with respect to electricity demand, initial generation and storage capacities, natural resource endowments and national energy policies. Natural resource endowments include the availability of lignite and biomass as well as hydro, wind and solar power. Due to the country-specific resolution, energy policy targets can be set on the national level or for a specified group of model regions (e.g. all EU Member States).

2.3. Temporal Resolution

In order to accommodate both long-term investment decisions and short-term fluctuations of wind, solar irradiance and demand, LIMES-EU makes use of two different time scales. The long-term scale ranges from 2010 to 2050 and is subdivided in 5-year *time steps*. The short-term scale subdivides the time steps into multiple *time slices*. Eight time slices - with a length of three hours each - add up to one representative day. A weighting factor is given to each representative day; together they add up to one model year. Assigning different weights to representative days allows for representing both days with common and rare load patterns. Section 3 presents the approach of how to select these representative model days.

While investments in generation, storage and transmission capacities are endogenously determined for each of the 5-year time steps, the balancing of electricity demand and supply, i.e. the dispatch of generation, storage and transmission capacities, is modeled for each time slice. The short-term perspective is needed to correctly value the available investment options by accounting for the intra-year variability of the electricity demand and intermittent renewable resources.

2.4. Technologies

The following briefly introduces the three kinds of technologies represented in LIMES-EU, namely generation, storage and transmission technologies. Section 4 provides a more detailed description of each technology. Power plants, transmission lines and storage facilities are not represented on a single unit basis in LIMES-EU, but are aggregated based on their economic and technical characteristics[3]. Modelling technology classes rather than individual units considerably simplifies the model, which otherwise could not be solved due to computational constraints.

Generation Technologies Generation technologies convert primary energies to electricity. There are 13 different generation technologies in LIMES-EU that classify into intermittent and dispatchable generation technologies. Wind onshore, wind offshore, solar photovoltaic (PV) and concentrated solar power (CSP) are intermittent with their availability varying both on a spatial and temporal scale. To account

[3] e.g. all hard coal power plants in France are aggregated to one class

for intra-regional differences in wind and solar resources, each model region is subdivided into three resource grades per intermittent generation technology. The availability of dispatchable technologies for each model region remains constant throughout the year. Dispatchable technologies in LIMES-EU comprise lignite, hard coal, natural gas combined cycle power plants and gas turbines as well as nuclear, biomass and hydro power plants. Electricity generation based on lignite, hard coal and natural gas is associated with CO_2 emissions. Optionally, those power plants can be enhanced with carbon capture and storage (CCS) technology that reduces their CO_2 emissions by storing them underground.

Transmission Technologies Transmission technologies enable the transfer of electricity between neighboring regions. Transmission is modelled as a transport problem from the center of one region to the center of a neighboring region - with the maximum transmissible amount of electricity being restricted by the installed net transfer capacity (NTC). The transmission of electricity between model regions is associated with losses. Network constraints and transmission losses within a region are not explicitly modelled in LIMES-EU ('copperplate' assumption).

Storage Technologies Demand and supply of electricity have to be balanced in every time slice. Storage technologies may serve as an additional consumer in times of oversupply of electricity from generation technologies and as an additional producer of electricity in times of undersupply. The shift of electricity provision from one time slice to another is subject to storage losses. Two different storage technologies are available in LIMES-EU: *intra*day and *inter*day storage. While intraday storages can only shift electricity provision between time slices of the same day, interday storages are able to shift electricity provision between all time slices of the same year. Compared to intraday storage, interday storage is subject to higher investment costs and higher storage losses.

3. Time Slice Approach

Long-term models with endogenous investments are computationally demanding, especially when optimizing intertemporally[4]. A common way to reduce temporal complexity is to optimize dispatch decisions only for a limited number of representative time slices instead of modelling every hour of the year. However, it is not obvious which time slices should be selected from historic data in order to preserve the characteristic variability of electricity demand and vRES infeed. Most existing approaches for aggregating historic data are only based on demand side fluctuations (Fürsch et al. 2011; Pina et al. 2011; Short et al. 2011) but as vRES technologies gain ever more importance in the European power system, models are required to also correctly accounting for their variability. Consequently, Blanford and Niemeyer (2011), Golling (2012), Nagl et al. (2013), Sisternes

[4] i.e. optimizing investment decisions for multiple time steps simultaneously

and Webster (2013) and others recently developed new approaches for selecting characteristic vRES infeed and demand situations. However, none of those are satisfyingly applicable to the present model as they either focus on only one RES technology or disregard different spatial compositions of load levels, which is pivotal in a multi-regional model.

We therefore developed a novel and reproducible algorithm to be applied for LIMES-EU (see Nahmmacher et al. 2014). In our case it is used for selecting representative days with a given number of eight diurnal time slices; however it can also be applied for selecting separate representative time slices or other groups of consecutive time slices. Due to its generic design, our method is applicable to all kinds of power system models with multiple fluctuating time series, i.e. models with multiple vRES technologies and/or multiple regions. The algorithm is meant to optimally fulfil three essential requirements, namely that the derived time slices should sufficiently reflect

- the annual electricity demand and average vRES capacity factors for each region,
- the load duration curve of each time series, and
- the spatial and temporal correlation of electricity demand and vRES infeed.

The first requirement ensures that the quality of a region with respect to solar and wind power is correctly reflected. By replicating both common and rare situations of load and vRES infeed as well as their respective frequency of occurrence (second requirement), the time slices neither overestimate nor underestimate single events. This serves to correctly value both base and peak load plants. The third requirement ensures that the characteristics of an interconnected multi-regional electricity system are correctly assessed and features such as large-area pooling and geographic smoothing are taken into account.

Our approach is based on Ward's (1963) hierarchical clustering algorithm. We apply this algorithm on historic electricity demand and weather data to group days with similar diurnal demand and vRES infeed patterns. As a result, each group of days is reflected by a representative day in the power system model.

3.1. Data

We use ENTSO-E (2013) data for the historic electricity demand levels and historic weather data from ECMWF (2012) for the vRES infeed. Using weather data rather than historic infeed data allows for taking into consideration a longer time span which prevents the overestimation of unusual years. The ECMWF data set comprises 33 years of ground solar irradiance and wind speed levels at 120m height for Europe. For every third hour between 1979 and 2011 the respective information is given for local data points in a spatial resolution of $0.75° \times 0.75°$. The conversion from weather data to vRES capacity factors is subject to the technology-specific power curves given in Section 4.

The three-hourly infeed of vRES technologies is averaged over all weather data grid cells belonging to the same region-specific resource grade. A comparison with real historic onshore wind feed-in levels however shows that realized capacity factors in mountainous countries[5] are much higher than the ones derived from the weather data. The spatial resolution of $0.75° \times 0.75°$ is obviously not high enough to reflect the variations in wind speeds between mountain valleys and ridges. As wind turbines are predominantly installed on ridges rather than in valleys we adjust the wind data in the following way:

$$\{v_{adj}\} = \{v_{era}\} + 0.01\,(\{h_{q3}\} - \{h_{mean}\}) \tag{2}$$

$$\text{with } [v] = m/s, [h] = m$$

It is assumed that the representative elevation h_{q3} of wind sites equals the third quartile of the elevation distribution within a weather data grid cell[6]. It is further assumed that the increase in local wind speed $(v_{adj} - v_{era})$ at a point within a grid cell is in direct proportion to the difference in elevation of this point to the average elevation h_{mean} of the grid cell. The increase of $0.01\frac{m/s}{m}$ is chosen in order to best reflect the infeed levels of wind power observed in 2010 and 2011 (derived from EUROSTAT (2013c) and EUROSTAT (2013b)).

Country-specific demand data is retrieved from ENTSO-E (2013a) in an hourly resolution. Compared to the vRES infeed, the intra-year demand fluctuations are less stochastic and follow distinct diurnal, intra-week and seasonal patterns. Though the absolute demand levels change between different years due to demographic and economic reasons, the relative intra-year fluctuations remain the same. The hourly demand data of 2010 and 2011 that is available for all model regions is therefore assumed to be representative for the *intra*-year demand side fluctuations between 1979 and 2011. Future *inter*-year growth of annual demand is subject to scenario assumptions (see Sections 5.1 and 6).

3.2. Clustering Approach

To select a limited number of characteristic days from the total of 12053 days between 1979 and 2011 for which the weather data is available we apply an approach based on the hierarchical clustering algorithm described by Ward (1963). The approach ultimately yields a set of representative days that minimizes the sum of squared errors between all observed days and their representatives. By employing a multidimensional clustering algorithm, the approximation of any load duration curve of a region's electricity demand or vRES infeed is optimized while at the same time accounting for the simultaneous load and vRES levels of the other model regions.

[5] Spain in particular but also Austria and Italy
[6] the distribution of elevation within a grid cell is based on NGDC (2013)

The distance between two days (observations) is defined as the Euclidean distance respecting a total of 3016 dimensions[7] per observation. Before starting the clustering algorithm all time series are normalized to their maximum value. Subsequently, the algorithm iteratively groups similar days together until only one cluster containing all days remains. In each step, the clustering is done in a way that minimizes the variance within each cluster. Figure 2 visualizes the clustering procedure of our data.

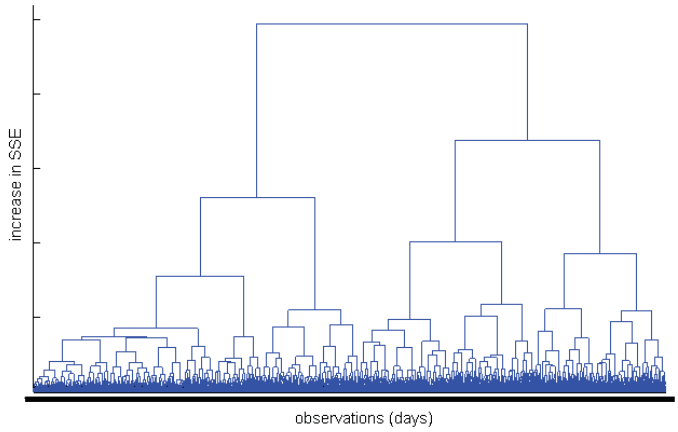


Figure 2: Dendrogram of clustering procedure. *Showing the consecutive grouping of two clusters to a joint cluster and the resulting increase in the overall sum of squared errors (SSE, y-axis). All days (x-axis) are consecutively grouped together until only one cluster is left.* Source: Own computation with model-specific data.

3.3. Resulting Time Slices

Once the clustering algorithm is finished, the model operator is free to choose the amount of clusters to use for the model and thereby trade off temporal resolution against computation time. For each cluster, there is one representative day in the model. We choose that day as representative day that is closest to the cluster's mean vector. In the model, a weighting factor is assigned to every representative day according to the number of days within its cluster. To ensure correct average demand levels and capacity factors per technology and region the time series are scaled if necessary.

In Nahmmacher et al. (2014) we analyze the differences in model results depending on the number of time slices. We show that already 48 time slices[8] are sufficient to reflect the characteristic fluctuations of electricity demand and vRES infeed in LIMES-EU. We therefore use 48 time slices in standard applications of the model.

[7] Each observation contains data about 29 regions, 4 technologies, 3 resource grades per technology and region as well as region-specific demand data; each for every third hour of the day.

[8] i.e. 6 representative days

4. Technology Characteristics

4.1. Generation Technologies

4.1.1. Intermittent Generation Technologies

Intermittent technologies comprise the generation technologies that are based on wind and solar power. For wind power LIMES-EU discerns between onshore and offshore power plants. Solar power technologies are divided into PV cells and CSP plants. Tables 1 and 2 give the techno-economic characteristics of these power plants. As the future development of their investment costs is highly uncertain, it is usually subject to a sensitivity analysis. Based on European Commission (2014) Table 2 gives the investment cost assumptions for our default scenario.

Table 1: Characteristics of wind and solar power plants

	Fixed O&M (%/a)	Lifetime (a)
Wind Onshore	3	25
Wind Offshore	5	25
PV	1	25
CSP	3	30

Source: Haller et al. (2012) and own assumptions

Table 2: Default assumptions for vRES investment costs (€/kW)

	Wind Onshore	Wind Offshore	PV	CSP
2010	1300	4750	2500	5500
2015	1296	4412	1700	4329
2020	1291	4073	1508	3158
2025	1262	3790	1297	2859
2030	1232	3507	1085	2560
2035	1212	3338	1011	2411
2040	1191	3168	937	2262
2045	1171	2999	862	2112
2050	1150	2829	788	1963

Source: European Commission (2014) and own assumptions

The output of intermittent generation technologies is constrained by the region- and time-slice-specific availability of their respective renewable energy sources and subject to technology-specific power curves. Power curves describe the relation between resource availability (wind speed or solar irradiance) and possible electricity production of a respective power plant.

Turbine-specific wind power curves are published by the respective turbine producers. However, using power curves of commonly installed wind turbines to derive capacity

factors from the weather data yields much higher values compared to historically realized full load hours (see Boccard (2009) for possible reasons). We therefore use the following regression to derive an aggregated wind power curve for the model (Equation 3). It is based on 2011-data of hourly German wind power production P_{Wind} (ÜNB 2013b) and installed capacities[9] cap_i (ÜNB 2013a) as well as the ERA-Interim wind speed data v_i (ECMWF 2012) per weather data grid cell i. It is assumed that the power output is proportional to the fifth power of the wind speed[10]. The resulting wind power curve which is defined by the five coefficients β_{1-5} is depicted in Figure 3.

$$P_{Wind} = \sum_i cap_i \left(\beta_1 v_i + \beta_2 v_i^2 + \beta_3 v_i^3 + \beta_4 v_i^4 + \beta_5 v_i^5\right) \tag{3}$$

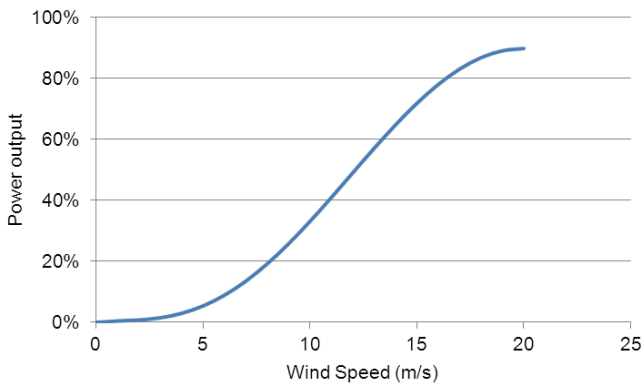


Figure 3: Aggregated wind power curve. Source: Own calculations based on ECMWF (2012); ÜNB (2013a,b).

The output of PV cells is assumed to be in a linear relation to the solar irradiance. In contrast to PV cells that use both direct and diffuse irradiance, CSP plants can only produce electricity from direct solar irradiance. Following Haller et al. (2012), the direct solar irradiance is derived from a simplified approximation which assumes that the direct normal irradiance DNI_i is a function of the global solar irradiance I_i and the latitude lat_i of the weather data grid cell i (Equation 4). This way the DNI share of global irradiance is 75% at a latitude of 30° and decreases for larger latitudes.

$$DNI_i = I_i \left(1 - 0.25 \left(\frac{lat_i}{30}\right)^{1.6}\right) \tag{4}$$

[9] The plant-specific installed capacities are aggregated according to the weather data grid.

[10] The power P of a free flowing wind stream is given by $P = \frac{1}{2}v^2\dot{m} = \frac{1}{2}v^2(vA\rho)$, with $\dot{m}$ denoting the mass flow rate, v the wind speed, ρ the air density and A the flow cross-section. Hence the power *input* of a wind turbine is proportional to the third power of the wind speed. The power *output* however is subject to a wind speed dependent power coefficient which is accounted for by also including the 4th and 5th power of v.

As in Haller et al. (2012) CSP plants are modelled with an collector area that is four times the size required to reach nominal output at reference conditions (SM4[11] configuration). Each CSP plant is equipped with an internal thermal storage with a capacity large enough to level out the diurnal fluctuations in solar energy input. Thus, even though solar irradiance varies between time slices, CSP plants are dispatchable within the limits of their daily availability factors that differ across days.

4.1.2. Dispatchable Generation Technologies

Power plants using fossil fuels, uranium, biomass or hydro power as a primary energy source are dispatchable within the limits of their annual availability. Except for hydro[12], the annual availability of these technologies is equal for all model regions. Table 3 gives an overview about the techno-economic characteristics of fuel and hydro based power plants in LIMES-EU.

Table 3: Techno-economic characteristics of thermal and hydro power plants

	Investment Costs (€/kW)	Efficiency new (old) (%)	Annual Availability (%/a)	Fixed O&M (%/a)	Variable O&M (€/MWh)	Minimum Load (%)	Lifetime (a)
Nuclear	4000	33	80	3	2.8	40	60
Hard Coal	1500	44 (37.4)	80	2	6.9	30	50
Hard Coal CCS	2600	38	80	2	11.4	30	50
Lignite	1800	43 (36.6)	80	2	9.1	50	50
Lignite CCS	3000	37	80	2	14.6	50	50
Gas CC	800	60	80	3	0.5	40	40
Gas CC CCS	1600	52	80	3	5.5	40	40
Gas GT	400	35	80	4	0.5	-	40
Biomass	2000	42	80	4	2.9	-	40
Hydro	2500	100	see Table 13	2	0	-	80

Source: European Commission (2014); Haller et al. (2012); Schmid et al. (2012); Schröder et al. (2013); own assumptions

Power plants with steam turbines are subject to minimum load restrictions and ramping constraints. In order to represent these characteristics in LIMES-EU, ramping of hard coal, lignite and natural gas combined cycle technologies is only allowed between model days. Within a model day their operating capacity has to remain constant throughout the day's eight time slices. Additionally, their electricity production may not fall below a minimum load that is defined as a share of operating capacity. Efficiency losses due to part load operation are disregarded. The operation of nuclear power plants is modelled in the same way. However, their operational capacity has to remain constant throughout the year. The minimum load restrictions are given in Table 3. Power plants with gas turbines are assumed to be able to ramp up and down within the time span of a single

[11] SM: solar multiple

[12] see Section 5.3.2 for the region-specific availability of hydro power plants

time slice. Minimum load restrictions for these generation technologies are therefore not considered.

The prices for primary energy sources used in thermal power plants are exogenous to LIMES-EU and thus independent from demand[13]; they are the same for every model region (see Table 4). However, the availability of certain fuels, namely lignite and biomass, differs between model regions (see Section 5.3.2).

Power generation from hard coal, lignite and natural gas is associated with greenhouse gas emissions; the CO_2 intensity of these primary energy sources is given in Table 4 as well. The stated emission factors are drawn from IPCC (1996) and are equal for every model region. In reality, the emission intensity of lignite significantly depends on the site of extraction and differs not only between but also within regions. However, for simplicity and due to the lack of sufficient data, we abstract from region-specific emission factors and adopt the approximation by IPCC (1996).

Table 4: Prices and CO_2 intensity of fuels

	Fuel prices (€/GJ)									CO_2 intensity
	2010	2015	2020	2025	2030	2035	2040	2045	2050	(tCO_2/TJ)
Uranium	0.5	0.6	0.7	0.8	1.0	1.2	1.4	1.7	2.0	0
Hard Coal	1.8	2.2	2.6	2.6	2.7	2.9	3.1	3.3	3.5	94.6
Lignite	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	101.2
Natural Gas	5.3	6.2	6.9	7.1	7.3	7.2	7.2	7.1	7.0	56.1
Biomass	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	0

Source: European Commission (2014); IPCC (1996); own assumptions

4.2. Transmission Technologies

Transmission expansion between countries is modelled endogenously in LIMES-EU. For enabling the joint optimization of generation, storage and transmission expansion within one model run the transmission grid is represented by 'net transfer capacities' (NTC). The NTC-approach abstracts from the complex power flows of the highly intermeshed European transmission network by stating a simple transport-problem for the electricity exchange between two neighbouring countries. The installed NTC between two countries defines the maximum tradable power flow within a given time slice and remains constant throughout the year. Higher power flows are possible after investing in transmission expansion and thereby increasing the NTC between two countries. Investment costs depend on the additional capacity to be installed and the distance between the two country-centers. Table 5 summarizes the techno-economic characteristics of NTCs applied in the model.

The specific NTC investment cost vary significantly in the literature: Instead of the 1M€/GWkm in Hirth (2013) and LIMES-EU, Schaber et al. (2012) and Fürsch et al.

[13] i.e. all model regions are assumed to be price takers on the fuel markets

(2013) only assume costs of 0.4M€/GWkm. However, 0.4M€/GWkm rather reflect the costs for thermal capactiy than for NTC: NEP (2013) state costs of 1.4M€/km for a 380kV overhead double-circuit. With a transfer capacity of about 1.8GW per circuit, this results in 0.4M€ per GWkm of thermal capacity (cf. DENA 2010; IZES et al. 2011). There are several reasons, why we assume the costs per NTC to be much higher: (1) NTC values are significantly smaller than thermal transfer capacities; (2) the stated costs only cover the lines and do not comprise substations and converters; and (3) costs for underground and sea cables are considerably higher than for overhead lines. We therefore assume that 1M€ per GWkm NTC is an appropriate approximation of the real transmission investment costs.

Table 5: Characteristics of transmission technologies

	Inv. Costs (M€/GWkm)	Availability (%)	Lifetime (a)	Losses (%/1000km)
Net Transfer Capacity	1.0	80	50	7

Source: Haller et al. (2012); NEP (2013); Short et al. (2011); own assumptions

4.3. Storage Technologies

The purpose of storage technologies is to level out the excess and deficit of electricity over time. In LIMES-EU we consider two generic storage technologies: *intra*day storage for balancing between time slices of the same day and the more expensive as well as less efficient *inter*day storage for balancing between time slices of the same year. The technical and economic features of the two storage options are given in Table 6. They are based on existing storage technologies, namely pumped-hydro for intraday storage and power-to-gas for interday storage. However, the parameters of these storage technologies only serve as a guidance for the two storage options in LIMES-EU. That is, we do not account for possible regional constraints[14] regarding these specific storage technologies, but implicitly assume that further options for intraday and interday storage with similar technical and economic parameters are available or will be in the future.

Neither the time slices of a respective day nor the representative days themselves are modelled in a fixed order. The capacity of a storage system is therefore only regarded in terms of possible power input and output, not in terms of storage size. While this approach significantly helps to reduce computation time it may overestimate the potential for interday storages by not regarding the required storage size. However, given the assumed cost and efficiency stated in Table 6 interday storages do not play a major role in any scenario outcome.

[14] e.g. suitable sites for pumped-hydro storage systems

Table 6: Characteristics of storage technologies

	Inv. Costs (€/kW)	Fixed O&M (%/a)	Efficiency (%)	Lifetime (a)
Intraday Storage	1500	1.0	80	80
Interday Storage	2000	1.0	40	40

Source: Fuchs et al. (2012); Haller et al. (2012); own assumptions

4.4. Depreciation of installed capacities

All technologies in LIMES-EU are characterized by technology-specific lifetimes. However, even before reaching their maximum lifetime, installed capacities are subject to degradation. This is implemented via the depreciation factor $\omega_{\tilde{t},te}$ which depends on the lifetime ψ_{te} of a technology te and the time $\tilde{t}$ that has passed since its installation (Equation 5). Only the share $\omega_{\tilde{t},te}$ of the installed capacity can be used for electricity generation, storage or transmission, respectively. Figure 4 visualizes the depreciation factor $\omega_{\tilde{t},te}$ for three different technological lifetimes: 20, 40 and 60 years.

$$\omega_{\tilde{t},te} = 1 - \left(\tilde{t}/\psi_{te}\right)^6 \qquad \forall te, \tilde{t} \leq \psi_{te} \tag{5}$$

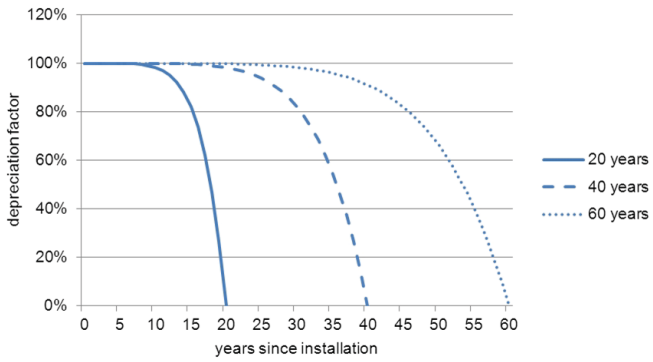


Figure 4: Depreciation factor ω for three different technological lifetimes (20, 40, 60 years). Source: Own assumptions.

5. Region-Specific Input Data

5.1. Electricity Demand

As discussed in Section 3, the intra-year variation of the model regions' electricity consumption is based on ENTSO-E (2013a). Final annual electricity demand for 2010 is retrieved from EUROSTAT (2013a) and IEA (2012b). Demand projections until 2050

are based on European Commission (2014) for default scenarios. Growth rates for model regions not mentioned in European Commission (2014) are estimated based on the growth rates of their neighboring countries for which data is available. Table 7 reports both the data for the base year 2010 and the default projections for future electricity demand. Regarding the year 2050, electricity consumption is projected to rise in every model region. However, the relative increase differs strongly across countries, with Germany (+12%) and Poland (+78%) being at the lower and upper end, respectively. An explanation of the region codes used in this document is given in Appendix B.

To account for intra-regional transmission and distribution losses, it is assumed that the required production of electricity has to exceed the reported final electricity consumption by 15% (cf. EUROSTAT 2014).

Table 7: Default assumptions for final electricity demand (in TWh)

	2010	2015	2020	2025	2030	2035	2040	2045	2050
AT	61.3	61.9	62.8	65.5	68	70	73	75.5	78.4
BE	83.3	84.7	83.6	83.5	87.2	90.4	96	101.8	105.3
BG	27.1	30.4	31.2	31.9	33.4	35.1	37.7	40.1	42.6
CZ	57.2	58.2	58.8	60.3	62.9	66	68.5	71.8	76.4
DE	529	529.5	522.6	526.2	541.5	546.3	557.3	575.7	591.6
DK	32.1	31.1	28.9	29.3	30.3	32.3	34.7	37.9	40.5
EE	6.9	8	8.3	8.6	9	9.4	9.6	10.2	10.7
ES	244.8	275.8	284.9	310	327.8	342.8	354	366.6	374
FI	83.5	81.7	82.2	82.4	84.3	87.9	91.9	95.9	100.4
FR	444.1	463.9	458	484.9	516.9	540.8	565.3	599.4	615.4
GB	328.3	333	322.3	330.1	340.5	355.3	382.6	404	410.3
GR	53.1	52.7	55	55.6	57	60.5	62.9	64.7	66.8
HR	15.9	16.4	17.4	17	18.1	19.1	20	21.3	22.2
HU	34.2	34.5	35.2	37.8	40.5	42	43.5	46.8	48.8
IE	25.2	26.7	27.1	29.5	32.4	35.4	37.7	40.1	42.7
IT	299.3	312.3	311.3	318.5	329.5	345.6	369.6	392	407.9
LT	8.3	9	9.1	9.5	10.5	11.2	12.1	12.8	13.4
LU	6.6	6.5	6.5	6.8	7.2	7.4	7.4	7.6	7.7
LV	6.2	7	7.3	7.9	8.3	8.9	9.7	10	10.1
NL	106.9	116.8	113.3	113.5	116.6	119.1	124.6	129.4	132.1
PL	118.5	137.2	158.6	168.1	175.3	182.8	193.1	207.2	212
PT	49.9	50.3	51.9	52.9	55.8	59.1	60.8	62.9	64.4
RO	41.3	48.1	51.2	52.8	54.7	57.8	60.4	65.2	66.7
SE	131.2	136.9	133.6	137.3	139.4	140.7	143.3	147.2	149.9
SI	12	13.6	14.7	15	15.3	15.4	15.9	16	16.3
SK	24.1	27.5	29.9	31.6	33.7	34.8	35.4	36.8	37.1
Balkan	57.7	61.4	64	66	68.8	72.4	75.7	80.3	83.3
CH	59.8	61.3	60.7	62.5	65.2	67.3	70.1	73.6	75.9
NO	113.5	118.4	115.5	118.7	120.5	121.6	123.9	127.2	129.6

Source: EUROSTAT (2013a); European Commission (2014); IEA (2012b); own assumptions

5.2. Installed Capacities in Base Year

For the model's base year 2010, installed capacities are set exogenously. The existing capacities of generation and storage technologies (see Table 8) as well as their age structure is derived from Platts (2011) and EUROSTAT (2013b). The base year's transmission network (Table 9) is reflected by the NTC summmer values of 2010 as reported by ENTSO-E (2013b). As the precise age structure of the transmission network is unknown, we assume that the existing lines were either constructed or refurbished after 1985 and that invesmtents into the grid were equally distributed between 1985 and 2010.

Table 8: Installed generation and storage capacities in 2010 (in GW)

	Intraday Storage	Nuclear	Hard Coal	Lignite	Natural Gas CC	Natural Gas GT	Hydro	Bio	Wind Onshore	Wind Offshore	PV	CSP
AT	2.01	0.00	1.41	0.00	4.79	0.46	10.07	0.46	1.00	0.00	0.10	0.00
BE	1.21	6.04	1.80	0.00	6.17	1.60	0.11	0.45	0.76	0.15	0.91	0.00
BG	1.06	2.00	2.04	3.32	0.52	0.12	1.87	0.01	0.50	0.00	0.03	0.00
CZ	1.15	3.90	1.75	7.21	0.54	0.65	0.98	0.03	0.22	0.00	1.97	0.00
DE	6.78	21.51	30.10	21.25	25.44	7.51	3.84	1.43	27.81	0.18	17.34	0.00
DK	0.00	0.00	4.57	0.00	2.76	1.70	0.00	0.52	2.81	0.84	0.01	0.00
EE	0.00	0.00	0.00	2.86	0.20	0.02	0.01	0.06	0.11	0.00	0.00	0.00
ES	4.01	7.73	9.72	0.00	30.39	5.83	14.04	0.50	22.65	0.00	4.03	0.68
FI	0.00	2.84	3.79	0.06	2.80	1.83	3.07	3.06	0.19	0.00	0.01	0.00
FR	4.52	65.88	7.48	0.00	8.88	6.22	19.98	0.15	4.59	0.00	0.89	0.00
GB	2.95	12.61	29.84	0.00	39.34	5.65	1.64	0.39	4.03	1.35	0.08	0.00
GR	0.62	0.00	0.00	5.13	5.21	2.04	2.51	0.01	1.38	0.00	0.21	0.00
HR	0.28	0.00	0.34	0.00	1.42	0.18	1.83	0.00	0.08	0.00	0.00	0.00
HU	0.00	2.00	0.09	1.10	3.62	0.87	0.05	0.14	0.29	0.00	0.00	0.00
IE	0.29	0.00	0.92	0.00	4.59	1.02	0.24	0.40	1.39	0.03	0.00	0.00
IT	5.94	0.00	12.27	0.00	62.64	5.75	15.33	0.84	6.02	0.00	3.69	0.00
LT	0.80	0.00	0.00	0.00	2.71	0.02	0.11	0.00	0.13	0.00	0.00	0.00
LU	1.10	0.00	0.00	0.00	0.39	0.10	0.04	0.00	0.04	0.00	0.03	0.00
LV	0.00	0.00	0.00	0.00	0.89	0.04	1.52	0.01	0.03	0.00	0.00	0.00
NL	0.00	0.50	4.02	0.00	14.64	2.65	0.04	0.16	2.05	0.25	0.09	0.00
PL	1.47	0.00	23.16	9.00	1.31	0.11	0.81	0.06	1.15	0.00	0.00	0.00
PT	0.97	0.00	1.88	0.00	4.49	1.79	3.95	0.16	3.80	0.00	0.13	0.00
RO	0.00	1.44	2.03	5.98	5.51	0.14	6.58	0.01	0.39	0.00	0.00	0.00
SE	0.43	9.63	0.36	0.00	3.33	2.00	16.48	2.19	1.88	0.13	0.01	0.00
SI	0.19	0.73	0.12	0.84	0.25	0.31	0.97	0.01	0.00	0.00	0.01	0.00
SK	0.86	1.95	0.61	0.56	1.21	0.19	1.56	0.00	0.00	0.00	0.02	0.00
Balkan	1.06	0.00	0.34	8.72	1.07	0.11	6.54	0.00	0.00	0.00	0.00	0.00
CH	1.42	3.34	0.00	0.00	0.15	0.27	12.48	0.03	0.04	0.00	0.11	0.00
NO	0.83	0.00	0.01	0.00	0.71	0.69	28.45	0.01	0.42	0.00	0.00	0.00

Source: EUROSTAT (2013b); Platts (2011)

Table 9: Transmission capacities between model regions

	Regions to which transmission connections are possible (existing net transfer capacities of 2010 in GW)
AT	CH (0.77), CZ (0.70), DE (1.60), HU (0.43), IT (0.14), SI (0.90), SK (0.00)
BE	DE (0.00), FR (2.10), LU (0.00), NL (2.25)
BG	Balkan (0.50), GR (0.45), RO (0.40)
CZ	AT (0.70), DE (1.45), PL (1.35), SK (1.60)
DE	AT (1.60), BE (0.00), CH (3.23), CZ (1.45), DK (1.83), FR (2.90), LU (0.98), NL (3.95), PL (1.00), SE (0.60)
DK	DE (1.83), NO (0.95), SE (1.86)
EE	FI (0.35), LV (0.50)
ES	FR (0.85), PT (1.20)
FI	EE (0.35), SE (1.85)
FR	BE (2.10), CH (2.05), DE (2.90), ES (0.85), GB (2.00), IT (1.64), LU (0.00)
GB	FR (2.00), IE (0.25), NL (0.00), NO (0.00)
GR	Balkan (0.28), BG (0.45), IT (0.50)
HU	AT (0.43), Balkan (0.60), HR (0.75), RO (0.55), SI (0.00), SK (0.83)
HR	Balkan (0.88), HU (0.75), SI (0.75)
IE	GB (0.25)
IT	AT (0.14), CH (2.45), FR (1.64), GR (0.50), SI (0.23)
LT	LV (1.18), PL (0.00)
LU	BE (0.00), DE (0.98), FR (0.00)
LV	EE (0.50), LT (1.18)
NL	BE (2.25), DE (3.95), GB (0), NO (0.7)
PL	CZ (1.35), DE (1.00), LT (0.00), SE (0.30), SK (0.55)
PT	ES (1.20)
RO	Balkan (0.45), BG (0.40), HU (0.55)
SE	DE (0.60), DK (1.86), FI (1.85), NO (3.62), PL (0.30)
SI	AT (0.90), HR (0.75), HU (0.00), IT (0.23)
SK	AT (0.00), CZ (1.60), HU (0.83), PL (0.55)
Balkan	BG (0.50), GR (0.28), HR (0.88), HU (0.60), RO (0.45)
CH	AT (0.77), DE (3.23), FR (2.05), IT (2.45)
NO	DK (0.95), GB (0.00), NL (0.70), SE (3.62)

Source: ENTSO-E (2013b); own assumptions

5.3. Resource Endowments

5.3.1. Wind & Solar

A country's wind and solar power potential is defined by two determinants: (1) the installable capacity of wind and solar power plants and (2) the achievable capacity factors at the respective sites.

The installable capacity is again determined by a set of three factors. First, by the area that is suitable for installing a specific technology; we derive the size of this area from land cover (FAO 2013) and elevation (NGDC 2013) data. However, due to public acceptance and competing usage possibilities only a certain share of this area is actually available for power production; this share is the second determining factor. And third, the amount

of capacity that can be installed on the available area is subject to technology-specific restrictions. Table 10 summarizes the parameters used to calculate the capacity potential for each technology.

Table 10: Assumptions for the approximation of regional wind and solar power potentials

	Suitable areas	Share of suitable areas available for RES	Maximum capacity density (MW/km^2) on available area
Wind Onshore	Agricultural areas	30%	4
	Forest areas	5%	
Wind Offshore	Marine areas - max. depth: 50m - max. distance to shore: 55km - within exclusive economic zone	50%	6
PV	Agricultural areas	2%	30
	Roof-tops & facades	50% ($12m^2$/capita)	100
CSP	Agricultural areas	2%	10

Note: Agricultural areas include cropland, meadows and pastures as well as fallow land.
Source: FAO (2013); Held (2010); IEA (2002); NGDC (2013); Trieb et al. (2009); VLIZ (2012); Denholm et al. (2009); Ong et al. (2013); own assumptions

Onshore wind turbines can be installed in forests and agricultural areas, which include cropland, meadows and pastures as well as fallow land (FAO 2013). The share of these areas that is available for wind power is mainly limited by public acceptance and nature reserves. Additional usage, such as food production on agricultural land, is still possible as the wake effect[15] considerably limits the maximum density of wind turbines per square kilometer.

Sites eligible for offshore wind power plants lie within a distance of less than 55km to the mainland and belong to the exclusive economic zone (VLIZ 2012) of the respective model region. Sites with a water depth of more than 50m are excluded. Additionally only a share of the resulting area may be used for offshore wind power to prevent wind turbines from being installed too close to the mainland shore or smaller islands as well as to account for shipping corridors.

In order to assess the installable capacity of solar PV, two kinds of PV systems are considered: large systems that are installed on agricultural areas and small PV systems mounted on rooftops and facades. In contrast to onshore wind power no other use of the land dedicated to solar power is possible, as the PV cells and the associated infrastructure cover most of the ground. For that reason, only a small share of a model region's agricultural area is eligible for large PV systems. Following IEA (2002) the available rooftop and facade area for small PV systems is approximated based on a model region's population. However, to account for the deployment of solar heating panels only half of the area potential stated in IEA (2002) is available for solar PV (cf. Held 2010).

[15] The wake effect describes the turbulence of the wind stream behind a turbine. This turbulence prohibits the installation of wind turbines in too close proximity.

Table 11: Installable capacities of wind and solar power plants per region (in GW)

	Wind Onshore	Wind Offshore	PV	CSP
AT	45.8	0.0	29.2	6.3
BE	17.7	9.1	21.4	2.7
BG	68.5	11.6	39.6	10.1
CZ	56.1	0.0	38.3	8.5
DE	222.6	83.6	200.4	33.4
DK	32.6	149.0	22.5	5.3
EE	15.8	55.9	7.3	1.9
ES	366.9	55.0	221.6	55.1
FI	71.8	130.5	20.3	4.6
FR	381.7	133.7	251.8	58.3
GB	212.5	312.4	179.3	34.4
GR	105.6	27.6	62.8	16.3
HR	19.8	47.1	13.4	2.7
HU	68.2	0.0	44.3	10.7
IE	56.3	52.2	32.9	9.1
IT	190.2	77.7	159.9	28.6
LT	37.6	9.2	20.7	5.5
LU	1.7	0.0	1.4	0.3
LV	28.4	43.1	13.6	3.6
NL	23.6	57.1	31.8	3.8
PL	193.9	40.7	134.4	29.2
PT	51.0	16.7	35.1	7.4
RO	183.0	24.3	111.2	28.3
SE	93.4	167.7	30.0	6.2
SI	8.3	0.3	5.4	1.0
SK	27.2	0.0	18.3	3.9
Balkan	134.7	5.3	83.7	20.1
CH	20.8	0.0	18.7	3.0
NO	32.2	122.2	12.0	2.0

Source: FAO (2013); Held (2010); IEA (2002); NGDC (2013); Trieb et al. (2009); VLIZ (2012); Denholm et al. (2009); Ong et al. (2013); own assumptions

Similar to large solar PV systems, CSP plants may only be installed on former agricultural area. However, as we assume a SM4 configuration[16] in LIMES-EU the maximum installable capacity per square kilometer is much smaller compared to PV systems.

To account for the varying quality of wind and solar sites within a country, we define three resource grades per intermittent renewable technology for every model region. Each resource grade comprises a certain share of the region's area and is assigned the average technology-specific capacity factor of this area[17]. The assignment is made in a way that the first resource grade comprises the best resource sites of a region that together add up to 10% of the region's area. The second resource grade comprises the next best sites that add up to 30% of the region's area. Consequently, the third resource grade contains 60% of a region's area subsuming the sites with the lowest capacity factors. The assignment

[16] see Section 4.1.1

[17] based on the data presented in Section 3.1 and the power curves from Section 4.1.1

Table 12: Maximum capacity factors of wind and solar power plants per region and resource grade (in %)

	Wind Onshore			Wind Offshore			PV			CSP		
	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
AT	19	16	12	-	-	-	12	12	11	6	6	5
BE	23	22	20	32	31	25	11	11	10	5	5	4
BG	21	14	9	20	18	16	14	14	13	8	8	7
CZ	20	18	16	-	-	-	11	11	11	5	5	5
DE	24	20	16	35	33	27	11	11	10	5	5	4
DK	33	31	26	36	33	29	11	10	10	4	3	3
EE	29	22	17	31	30	25	10	9	9	3	3	2
ES	25	16	11	32	22	11	17	17	15	11	10	9
FI	21	14	12	32	29	22	9	8	7	2	2	1
FR	28	21	14	33	29	21	14	13	12	8	7	5
GB	39	32	26	41	37	31	11	10	9	5	4	3
GR	19	14	8	28	21	11	16	16	15	11	10	9
HR	21	16	8	17	14	10	14	13	12	8	7	6
HU	14	12	9	-	-	-	13	13	12	6	6	6
IE	40	34	25	42	40	34	10	10	9	4	4	3
IT	20	15	9	18	15	10	17	15	13	11	9	7
LT	21	19	17	29	28	23	10	10	9	3	3	3
LU	21	21	20	-	-	-	11	11	11	5	5	5
LV	25	21	17	29	29	25	10	10	9	3	3	3
NL	29	25	20	35	33	29	11	11	10	4	4	4
PL	24	19	17	33	30	26	11	10	10	5	4	4
PT	21	16	12	26	23	19	17	17	16	11	10	9
RO	18	13	9	20	19	17	13	13	12	7	7	6
SE	24	18	13	32	30	23	10	9	8	3	2	1
SI	12	11	8	4	4	4	13	12	12	6	6	6
SK	16	15	13	-	-	-	12	11	11	6	5	5
Balkan	18	14	9	15	13	8	14	14	13	9	8	7
CH	19	15	9	-	-	-	13	12	12	6	6	6
NO	29	23	16	35	31	23	9	8	7	2	2	1

Source: ECMWF (2012); own assumptions

of resource grades is done separately for every technology that is based on wind and solar power. Table 11 shows the technologies' capacity potentials per model region; the corresponding capacity factors per region and resource grade are given in Table 12.

5.3.2. Fuels & Hydro

As stated in Section 4.1.2, fuel prices are the same for every model region. However, the availability of certain fuels differ between regions. Hard coal, natural gas and uranium are available to every model region in unrestricted quantities. Lignite and biomass, however, can only be consumed in their country of origin. LIMES-EU does not allow for trade of these fuels as the calorific value of both lignite and many biofuels is too low for a cost-efficient long-distance transport. Not all regions have lignite resources; the consumption

Table 13: Regional biomass and hydro potential

	Biomass			Hydro	
	Annual primary energy potential (in PJ)			Installable capacity (GW)	Annual availability (%/a)
	2010	2020	2030 -2050		
AT	96	109	121	11.1	44
BE	97	97	97	0.1	37
BG	19	33	39	2.2	20
CZ	53	63	70	1.2	26
DE	432	472	603	3.9	60
DK	77	77	77	0.0	30
EE	21	31	36	0.0	49
ES	230	307	350	14.7	25
FI	134	137	131	3.4	50
FR	438	519	662	22.6	37
GB	229	265	342	2.2	34
GR	22	47	53	2.5	23
HR	34	36	39	1.8	39
HU	50	63	78	0.1	46
IE	15	17	18	0.2	37
IT	226	261	346	15.3	35
LT	57	106	138	0.1	43
LU	3	3	3	0.0	39
LV	18	27	33	1.5	23
NL	145	145	145	0.1	32
PL	332	461	548	1.2	29
PT	50	54	57	5.5	30
RO	129	165	204	7.4	31
SE	163	181	188	17.2	46
SI	25	24	25	1.4	44
SK	31	33	50	2.0	32
Balkan	64	92	109	6.5	30
CH	34	40	49	12.5	34
NO	103	112	116	30.2	52

Source: EEA (2006); EUROSTAT (2013b,c); European Commission (2013b); FAO (2013); own assumptions

of lignite is therefore limited to those countries with existing lignite mines in 2010. In addition, we assume that new open-cast mines for lignite extraction are only opened when others are closed; hence, the maximum annual consumption of lignite is fixed to 2010 levels.

The bioenergy potential is based on EEA (2006) which states the environmentally sustainable biomass potential for the EU25 Member States. We assume that two thirds of the environmentally sustainable biomass potential can be deployed at competitive prices and that the transport and heat sector demand about 50% of the available biomass stock. Therefore, only one third of the potential stated in EEA (2006) is considered eligible for electricity production in LIMES-EU. Biomass potentials of countries for which no data is available in EEA (2006) are calculated based on the extent of arable land and forests

in these countries (FAO 2013) as well as the land structure and biomass potential of the surrounding countries with available data. In case the potential calculated for a specific country is smaller than its biomass deployment target stated in the NREAPS[18] (European Commission 2013b), the potential is adjusted to cover this target[19]. Table 13 shows the maximum deployment of biomass per model region.

The limited availability of sites suitable for deploying hydro power is reflected by a maximum installable capacity of hydro power plants. As the potential for further hydro power capacities is low in most European countries, capacity additions are only allowed up to the level needed to fulfil the national targets for electricity production from hydro as stated in the NREAPS (European Commission 2013b). In addition to the maximum installable capacity, the capacity factors of hydro power plants also vary among model regions. As the availability of hydro power varies significantly between years, we use an average of the realized capacity factors between 2006 and 2010 that are derived from EUROSTAT (2013c) and EUROSTAT (2013b). Both maximum capacities and capacity factors are given in Table 13.

6. Implementation of Policies

The model allows for implementing climate and energy policy targets by including constraints on CO_2 emissions or on the deployment of certain technologies. Targets can be set for single countries or for aggregate regions such as the EU Member States. A differentiation and analysis of different policy *instruments* is not possible: As LIMES-EU is a social planner optimization model with perfect foresight, policy targets will always be fulfilled in a cost-optimal way. Hence, results from LIMES-EU provide useful benchmarks on the future development of the European electricity system, but potentially underestimate important obstactles such as public acceptance or institutional capacity (cf. Hughes and Strachan 2010).

Climate Policy The standard scenario reflects the CO_2 emission reduction targets set on EU level as stated in the EU Low Carbon Roadmap (European Commission 2011a). For the electricity sector the Roadmap targets translate to an emission reduction of about 95% below 1990 levels[20] until 2050 (European Commission 2011b). If the non-EU model regions Norway, Switzerland and Balkan are not subject to these emission reduction commitments, individual targets can be defined for those regions. Alternatively, an emission intensity constraint can be set for regions without a dedicated climate policy. In such a case, a region's emission intensity (based on the region's domestic consumption of electricity) is limited to its 2010 level. This prevents artifactual model results showing a massive import of electricity into the

[18] National Renewable Energy Action Plans (see Section 6)
[19] This is the case for Denmark, the Netherlands, Belgium and Luxemburg
[20] 1990 emission levels of the model regions' electricity sector have been calculated based on IEA (2012a)

EU from CO_2 emitting power plants sited in non-policy regions. Instead of constraining the CO_2 emissions for single countries or aggregated regions, LIMES-EU also allows for setting a region-speicfic price on CO_2 emissions. If a constraint on CO_2 emissions is set, the corresponding price of an emission allowance can be derived from the constraint's shadow price, which is part of the model results.

Renewable Policy As stated by the European Parliament and European Council (2009) the EU Member States are committed to increase the share of renewable energy sources in their energy consumption by 20% until 2020. The Member States' National Renewable Energy Action Plans (NREAPS) specify how to reach the corresponding targets for the electricity sector on a national level and give technology-specific projections for the electricity generation until 2020 (European Commission 2013b). LIMES-EU allows for implementing such technology-specific renewable energy targets for single model regions as well as implementing technology unspecific targets on EU or country level. Targets are implemented as lower bounds on electricity production from these technologies.

Energy Efficiency Policy Energy efficiency translates to less electricity demand as compared to the reference scenario. As the electricity demand is given exogenously its reduction is not part of the optimization but set exogenously as well.

Nuclear & CCS Policy In several countries nuclear power plants and CCS technology face problems in public acceptance due to environmental risks and uncertain overall costs. In order to accomodate this, their future deployment is constrained by upper limits on investments in the two technologies. These limits can be set for each model region separately.

7. Model Validation

The purpose of LIMES-EU is to produce cost-efficient scenarios with regard to future investments into the European power system. Validating a long-term social planner model is conceptually challenging as the model does not aim to replicate historic developments but is designed to generate a socially optimal benchmark without considering real world market failures.

According to Schwanitz (2013), the primary aim of a validation is to build trust in the model. In this regard, a comprehensive documentation of the model, its equations and underlying assumptions as pursued in this paper is an important first step. Next to a thorough documentation of the model, a validation may include a discussion of illustrative model results and cross-checking them with stylized facts (Schwanitz 2013). Barlas (1996) suggests that a model is valid if it demonstrates 'the right behavior for the right reason'.

A full-fledged validation is beyond the scope of this document. Nevertheless, complementary to the documentation of the model structure and its parameter values, this Section

aims to build further trust in the model and to make its reasoning more accessible. First, we compare model results for the base year 2010 with historic data, namely the electricity generation mix and CO_2 emissions. In a second step, we compare long-term scenarios - the main focus of LIMES-EU - with results from other long-term models.

7.1. Comparison with Historic Data

For the base year 2010, only the dispatch of generation, storage and transmission technologies is optimized by LIMES-EU. The installed capacities are given exogenously. In this Section we compare the dispatch resulting from LIMES-EU with historic electricity production data from EUROSTAT (2014) and IEA (2014). In addition, we compare the resulting national CO_2 emissions with the historic emissions of 2010 (IEA 2012a).

In order to replicate the historic dispatch, we constrain the aggregated CO_2 emissions of the EU ETS countries according to their actual electricity sector emissions in 2010. The shadow price of this constraint amounts to 15.24€ which is consistent with the price for EU ETS allowances in this year: The average clearing price of emission allowance auctions in Germany was 14.36€ in 2010 (DEHSt 2010). Figure 5 shows both historic emissions and model results for 2010. Despite the simplifying model assumptions, the fit between historic emissions and model results is quite good. Only model results for France show a large deviation from historic data.

The reason for this deviation can be explained by Figure 6, which gives the historic and model based electricity generation mix of each region and of the EU28 Member States in total. The electricity mix of France is only slightly different between model and reality, with a small share of electricity provided by hard coal and natural gas fired power plants in reality. However, as most of the electricity in France is produced from carbon free energy sources, this difference has a large impact on absolute the emission outcome. The non-existence of fossil fuel based electricity generation in the model results for France can at least partly be explained by the missing representation of combined heat and power (CHP) plants in LIMES-EU. We refrain from including it in LIMES-EU as a sound implementation of CHP would make the model considerably more complex. However, in case CHP is assumed to be an important pillar of the future European electricity system, it could be approximated in LIMES-EU by a must run constraint of selected thermal power generation technologies.

As can be seen on the very left bars in Figure 6, the aggregated electricity mix of the EU28 is well reproduced by the model. Only lignite is somewhat overrated while hydro is used less compared to reality. The result that hydro power is used less in LIMES-EU compared to 2010 data can be explained by the fact that the availability factor of hydro power in LIMES-EU is based on the years 2006 to 2010. However, 2010 was an exceptionally good year for hydro power, with a capacity factor of 45% instead of the average 30% in Portugal and 51% instead of 39% in Croatia (EUROSTAT 2013b,c).

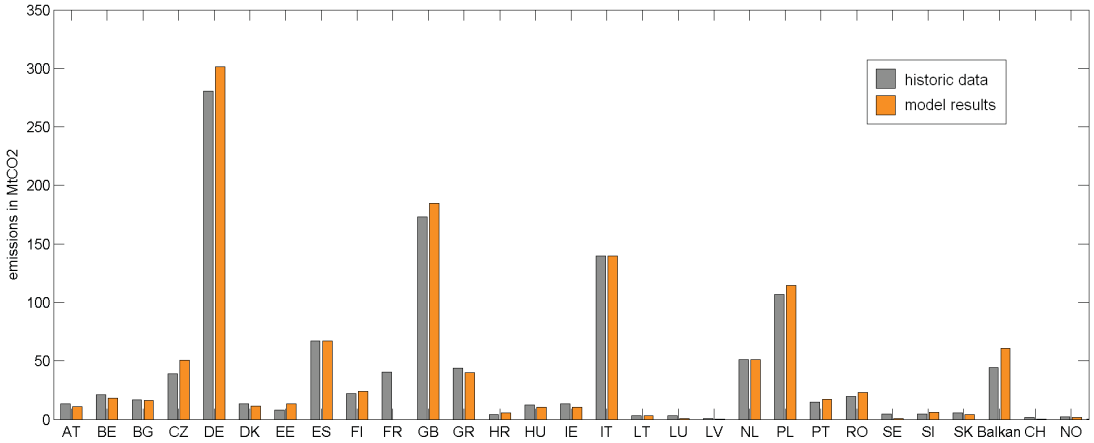


Figure 5: Comparison of historic and model-derived region-specific CO_2 emissions in 2010. Source: IEA (2012a); own model results.

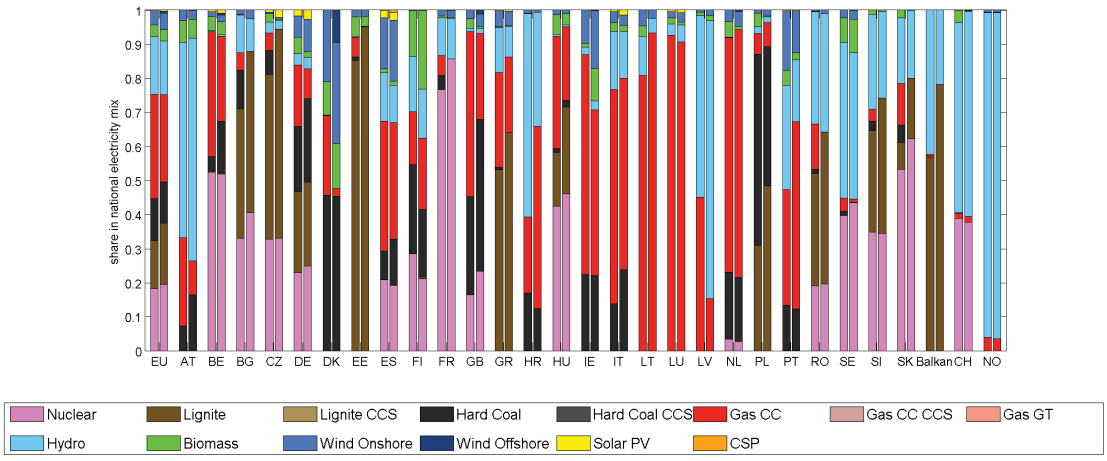


Figure 6: Comparison of the historic (*left bar*) and the model-derived (*right bar*) region-specific electricity generation mix in 2010. Source: EUROSTAT (2014); IEA (2014); own model results.

However, some regional electricity mixes deviate strongly from historic data, e. g. natural gas is overrated in Croatia but underrated in the United Kingdom. This is due to the fact that the model abstracts from regional differences in prices for primary energy sources as well as taxes and charges. It optimizes the overall European electricity system, without taking into account market failures that might distort the cost-efficient outcome in reality. This certainly is a drawback when aiming at reproducing historic market outcomes, but it is reasonable in order to derive benchmarks for the cost-efficient future development of the European electricity system.

7.2. Comparison with Other Models

In this Section we compare results derived from LIMES-EU with results from six other long-term models[21] with a distinct representation of the European electricity sector. As there is no real data about future years, setting the results of LIMES-EU into context with those of other models is deemed to be an appropriate way in order to build further trust in the model. The models we consider were part of a model comparison performed by the Energy Modeling Forum 28 (EMF28) focusing on scenarios for reducing Europe's CO_2 emissions until 2050 by 80%[22] (Knopf et al. 2013). Further scenario assumptions such as investment and fuel costs were not harmonized among the models. For LIMES-EU we therefore use the default parameter assumptions as stated in this documentation.

Figure 7 shows the cost-efficient capacity investment and electricity generation pathway until 2050 for the given CO_2 reduction target and the presented parameter assumptions. Note that the deployment of natural gas fired power plants is very sensitive to the price spread between natural gas and hard coal and should typically be covered by a sensitivity analysis. However, as Knopf et al. (2013) only give results for the year 2050, we do only compare results for this year; and the dominant role of natural gas has already passed at that time.

Figure 8 presents a comparison of regional model results from LIMES-EU and Knopf et al. (2013) for the year 2050. It shows the share of different generation technologies in the electricity mix of selected countries - namely France, Germany, Italy, Sweden and the United Kingdom. In addition, the Figure indicates the average EU28 shares derived from LIMES-EU in comparison to the shares stated in European Commission (2014).

The regional results from LIMES-EU fit very well into the range of the other models. Also the average EU28 shares are consistent with those from European Commission (2014); only solar power is significantly higher in LIMES-EU. The high share of solar in 2050 is based on a substantial addition of PV and CSP capacities after 2035 (cf. Figure 7). This rapid capacity addition is cost-efficient under the given assumptions, but may be deemed infeasible in reality. In this case, it is possible to set constraints on the maximum annual investments per region and technology in LIMES-EU.

Overall, the results suggest that LIMES-EU is well suited for generating meaningful long-term scenarios for the European electricity sector. Moreover, the model not only produces long-term results; the intertemporal optimization allows for analyzing the entire investment pathway from today until 2050. A sound assessment of the technologies' cost-efficient role in the future European power system is ensured by effectively accounting for short-term variability in the long-term optimization.

[21] FARM EU, POLES, PRIMES, TIMES PanEU, PET and EMELIE-ESY
[22] translating to about 95% for the electricity sector

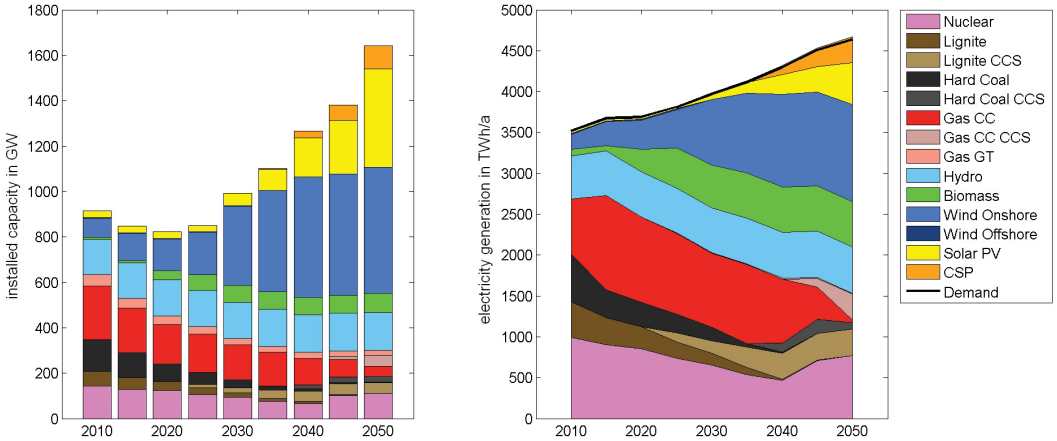


Figure 7: Cost-efficient pathway of the capacity and generation mix from 2010 to 2050. Source: Own model results.

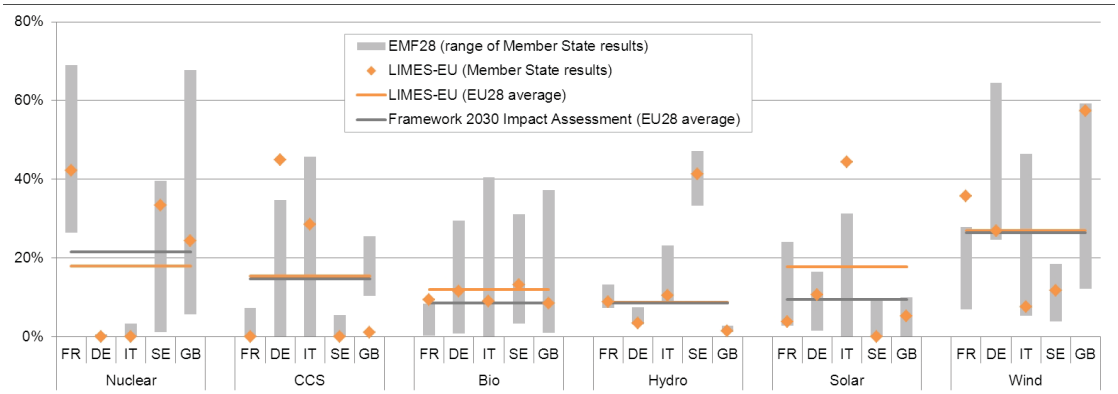


Figure 8: Share of generation technologies in the 2050 electricity mix. Source: European Commission (2014); Knopf et al. (2013); own model results.

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A. Model Equations

This Section provides a comprehensive list of all model equations. The Tables A.1 to A.4 give an overview about the symbols for indices, sets, parameters and variables used in the equations. All variables are constrained to be non-negative.

Table A.1: Indices

Symbol	Description
t	years
day	days
τ	time slices
r	regions
rg	vRES resource grades
te	electricity generation technologies
st	storage technologies
cn	transmission connections
pe	primary energy types

Table A.2: Sets

Symbol	Description
R	all regions
R^{pol}	regions with a common policy
T	all time slices
T_{day}	time slices of a specific day
TE	all electricity generation technologies
TE_{pe}	electricity generation technologies working with pe
TE_{pe}^{ccs}	CCS equipped electricity generation technologies working with pe
TE^{disp}	dispatchable electricity generation technologies
TE^{ramp}	thermal electricity generation technologies with ramping constraints
TE^{res}	RES technologies
TE^{vres}	vRES technologies
ST	all storage technologies
$ST^{interday}$	interday storage technologies
$ST^{intraday}$	intraday storage technologies
CN	all transmission connections
CN_r^{out}	transmission connections defined as starting in region r
CN_r^{in}	transmission connections defined as ending in region r

Table A.3: Parameters

Symbol	Description
ρ	discount rate
Δt	time span (in years) between model years
l_τ	length of time slice τ
λ_{pe}	emission factor of primary energy pe
ψ_{te}, ψ_{cn}	lifetime of technology te / connection cn
μ_{te}	minimum load of technology te
ϕ_r	minimum share of domestic electricity supply for region r
$c^I_{t,te}$, $c^I_{t,cn}$	capacity-specific investment cost
$c^F_{t,pe}$	energy-specific fuel cost
c^{OMF}_{te}	fixed operation and maintenance cost
c^{OMV}_{te}	variable operation and maintenance cost
$c^{CO_2}_{t,r}$	CO_2 emission cost
$\nu_{\tilde{t},te}$, $\nu_{\tilde{t},cn}$	salvage value factor
$\omega_{\tilde{t},te}$, $\omega_{\tilde{t},cn}$	depreciation factor
$d_{t,\tau,r}$	electricity demand
$\alpha^{vRES}_{\tau,r,te,rg}$, $\alpha_{r,te}$, α_{cn}	availability factor
η_{te}	conversion efficiency
γ_{cn}	transmission losses
$p^{max}_{t,r,pe}$	maximum primary energy consumption
cap^{CCScum}_r	maximum cumulated CCS potential
res_t, $res_{t,te}$, $res_{t,r}$, $res_{t,r,te}$	target for minimum electricity production from RES
$cap^{CO_2}_t$, $cap^{CO_2}_{t,r}$	target for maximum CO_2 emissions
cap^{CO_2cum}, $cap^{CO_2cum}_r$	target for maximum cumulated CO_2 emissions

Table A.4: Variables

Symbol	Description
C^{tot}	total system cost
C^I_t	investment cost
C^F_t	fuel cost
C^{OM}_t	operation and maintenance cost
$C^{CO_2}_t$	CO_2 emission cost
V	salvage value
$P_{t,\tau,r,pe}$	primary energy consumption
$K_{t,r,te}$, $K_{t,cn}$, $K_{t,r,st}$	installed capacity
$\Delta K_{t,r,te}$, $\Delta K_{t,cn}$, $\Delta K_{t,r,st}$	new capacity
$K^{RG}_{t,r,te,rg}$	installed capacity (resource grade specific)
$\Delta K^{RG}_{t,r,te,rg}$	new capacity (resource grade specific)
$G_{t,\tau,r,te}$	electricity generation
$E^{CO_2}_{t,r}$	CO_2 emissions
$E^{CCS}_{t,r}$	captured CO_2 (via CCS)
$S^{OUT}_{t,\tau,r,te}$	storage output
$S^{IN}_{t,\tau,r,te}$	storage input
$F^+_{t,\tau,cn}$, $F^-_{t,\tau,cn}$	transmission flow in positive / negative direction
$OP_{t,\tau,r,te}$, $OP_{t,day,r,te}$, $OP_{t,r,te}$	operating (running) capacity

A.1. Objective function and its components

Equation A.1: Objective function

$$C^{tot} = \sum_{t} \left(\Delta t \, e^{-\rho(t-t_0)} \left(C_t^I + C_t^F + C_t^{OM} + C_t^{CO_2} \right) \right) - e^{-\rho(t_{end}-t_0)} \, V \tag{A.1}$$

Equation A.2: Fuel costs

$$C_t^F = \sum_{r,pe} c_{t,pe}^F \sum_{\tau} l_\tau \, P_{t,\tau,r,pe} \qquad \forall t \tag{A.2}$$

Equation A.3: Investment costs

$$C_t^I = \sum_{r,te} \left(c_{t,te}^I \, \Delta K_{t,r,te} \right) + \sum_{r,st} \left(c_{t,st}^I \, \Delta K_{t,r,st} \right) + \sum_{cn} \left(c_{t,cn}^I \, \Delta K_{t,cn} \right) \qquad \forall t \tag{A.3}$$

Equation A.4: Operation and maintenance costs

$$C_t^{OM} = \sum_{r,te} \left(c_{te}^{OMF} \, c_{t,te}^I \, K_{t,r,te} + c_{te}^{OMV} \sum_{\tau} l_\tau \, G_{t,\tau,r,te} \right) + \sum_{r,st} c_{st}^{OMF} \, c_{t,st}^I \, K_{t,r,st} \qquad \forall t \tag{A.4}$$

Equation A.5: Emission costs

$$C_t^{CO_2} = \sum_{r} c_{t,r}^{CO_2} \, E_{t,r}^{CO_2} \qquad \forall t \tag{A.5}$$

Equation A.6: Salvage value

$$\begin{aligned} V = & \Delta t \sum_{te,r} \sum_{\tilde{t}=0}^{\psi_{te}} \nu_{\tilde{t},te} \, c_{(t_{end}-\tilde{t}),te}^I \, \Delta K_{(t_{end}-\tilde{t}),r,te} \\ & \Delta t \sum_{st,r} \sum_{\tilde{t}=0}^{\psi_{st}} \nu_{\tilde{t},st} \, c_{(t_{end}-\tilde{t}),st}^I \, \Delta K_{(t_{end}-\tilde{t}),r,st} \\ & + \Delta t \sum_{cn} \sum_{\tilde{t}=0}^{\psi_{cn}} \nu_{\tilde{t},cn} \, c_{(t_{end}-\tilde{t}),cn}^I \, \Delta K_{(t_{end}-\tilde{t}),cn} \end{aligned} \tag{A.6}$$

A.2. Electricity balance

Equation A.7: Electricity balance

$$\begin{aligned} d_{t,\tau,r} = &\sum_{te} G_{t,\tau,r,te} + \sum_{st} \left(S^{OUT}_{t,\tau,r,st} - S^{IN}_{t,\tau,r,st}\right) \\ &+ \sum_{cn \in CN^{in}_r} \left((1-\gamma_{cn})\, F^{+}_{t,\tau,cn} - F^{-}_{t,\tau,cn}\right) \\ &+ \sum_{cn \in CN^{out}_r} \left((1-\gamma_{cn})\, F^{-}_{t,\tau,cn} - F^{+}_{t,\tau,cn}\right) \qquad \forall t,\tau,r \end{aligned} \tag{A.7}$$

A.3. Equations for generation technologies

Equation A.8: Expansion and depreciation of generation technologies

$$K_{t,r,te} = \Delta t \sum_{\tilde{t}=0}^{\psi_{te}} \omega_{\tilde{t},te} \Delta K_{(t-\tilde{t}),r,te} \qquad \forall t,r,te \tag{A.8}$$

Equation A.9: Expansion and depreciation of vRES technologies per resource grade

$$K^{RG}_{t,r,te,rg} = \Delta t \sum_{\tilde{t}=0}^{\psi_{te}} \omega_{\tilde{t},te} \Delta K^{RG}_{(t-\tilde{t}),r,te,rg} \qquad \forall t,r,te \in TE^{vres}, rg \tag{A.9}$$

Equation A.10: Expansion of vRES technologies in regions and resource grades

$$\Delta K_{t,r,te} = \sum_{rg} \Delta K^{RG}_{t,r,te,rg} \qquad \forall t,r,te \in TE^{vres} \tag{A.10}$$

Equation A.11: Capacity constraint for all generation technologies

$$G_{t,\tau,r,te} \leq K_{t,r,te} \qquad \forall t,\tau,r,te \tag{A.11}$$

Equation A.12: Availability of Wind Onshore, Wind Offshore and PV

$$G_{t,\tau,r,te} \leq \sum_{rg} \alpha^{vRES}_{\tau,r,te,rg}\, K^{RG}_{t,r,te,rg} \qquad \forall t,\tau,r,te \in \{\textit{Wind Onshore, Wind Offshore, PV}\} \tag{A.12}$$

Equation A.13: Availability of CSP

$$\sum_{\tau \in T_{day}} l_\tau\, G_{t,\tau,r,te} \leq \sum_{\tau \in T_{day}} l_\tau \sum_{rg} \alpha^{vRES}_{\tau,r,te,rg}\, K^{RG}_{t,r,te,rg} \qquad \forall t, day, r, te \in \{CSP\} \tag{A.13}$$

Equation A.14: Availability of Hydro

$$G_{t,\tau,r,te} \leq 1.25\, \alpha_{r,te}\, K_{t,\tau,r,te} \qquad \forall t, r, te \in \{Hydro\} \tag{A.14}$$

Equation A.15: Annual availability of dispatchable generation technologies

$$\sum_{\tau} l_\tau\, G_{t,\tau,r,te} \leq \sum_{\tau} l_\tau\, \alpha_{r,te}\, K_{t,r,te} \qquad \forall t, r, te \in TE^{disp} \tag{A.15}$$

Equation A.16: Operation constraint for thermal generation technologies

$$OP_{t,\tau,r,te} \leq K_{t,r,te} \qquad \forall t, \tau, r, te \in TE^{ramp} \tag{A.16}$$

Equation A.17: Generation constraint for thermal generation technologies

$$G_{t,\tau,r,te} \leq OP_{t,\tau,r,te} \qquad \forall t, \tau, r, te \in TE^{ramp} \tag{A.17}$$

Equation A.18: Minimum load constraint for thermal generation technologies

$$G_{t,\tau,r,te} \geq \mu_{te}\, OP_{t,\tau,r,te} \qquad \forall t, \tau, r, te \in TE^{ramp} \tag{A.18}$$

Equation A.19: Ramping constraint for hard coal, lignite and natural gas combined cycle power plants

$$OP_{t,\tau \in T_{day},r,te} = OP_{t,day,r,te} \qquad \forall t, \tau, r, te \in \{Hard\ Coal,\ Lignite,\ Natural\ Gas\ CC\} \tag{A.19}$$

Equation A.20: Ramping constraint for nuclear power plants

$$OP_{t,\tau,r,te} = OP_{t,r,te} \qquad \forall t, \tau, r, te \in \{Nuclear\} \tag{A.20}$$

A.4. Equations for transmission technologies

Equation A.21: Expansion and depreciation of transmission capacity

$$K_{t,cn} = \Delta t \sum_{\tilde{t}=0}^{\psi_{cn}} \omega_{\tilde{t},cn} \Delta K_{(t-\tilde{t}),cn} \qquad \forall t, cn \tag{A.21}$$

Equation A.22: Transmission constraint

$$\begin{aligned} F^{+}_{t,\tau,cn} &\leq \alpha_{cn}\, K_{t,cn} \qquad \forall t, \tau, cn \\ F^{-}_{t,\tau,cn} &\leq \alpha_{cn}\, K_{t,cn} \qquad \forall t, \tau, cn \end{aligned} \tag{A.22}$$

A.5. Equations for storage technologies

Equation A.23: Expansion and depreciation of storage technologies

$$K_{t,r,st} = \Delta t \sum_{\tilde{t}=0}^{\psi_{st}} \omega_{\tilde{t},st} \Delta K_{(t-\tilde{t}),r,st} \qquad \forall t, r, st \tag{A.23}$$

Equation A.24: Storage constraint

$$\begin{aligned} S^{IN}_{t,\tau,r,st} &\leq K_{t,r,st} \qquad \forall t, \tau, r, st \\ S^{OUT}_{t,\tau,r,st} &\leq K_{t,r,st} \qquad \forall t, \tau, r, st \end{aligned} \tag{A.24}$$

Equation A.25: Interday storage balance

$$\eta_{st} \sum_{\tau} l_\tau \, S^{IN}_{t,\tau,r,st} = \sum_{\tau} l_\tau \, S^{OUT}_{t,\tau,r,st} \qquad \forall t, r, st \in ST^{interday} \tag{A.25}$$

Equation A.26: Intraday storage balance

$$\eta_{st} \sum_{\tau \in T_{day}} l_\tau \, S^{IN}_{t,\tau,r,st} = \sum_{\tau \in T_{day}} l_\tau \, S^{OUT}_{t,\tau,r,st} \qquad \forall t, day, r, st \in ST^{intraday} \tag{A.26}$$

A.6. Primary energy demand and CO_2 emissions

Equation A.27: Primary energy demand

$$P_{t,\tau,r,pe} = \sum_{te \in TE_{pe}} G_{t,\tau,r,te} / \eta_{te} \qquad \forall t, \tau, r, pe \tag{A.27}$$

Equation A.28: Primary energy constraint

$$\sum_{\tau} l_\tau \, P_{t,\tau,r,pe} \leq p^{max}_{t,r,pe} \qquad \forall t, r, pe \tag{A.28}$$

Equation A.29: CO_2 emissions from electricity generation

$$E^{CO_2}_{t,r} = \sum_{pe} \lambda_{pe} \sum_{\tau} l_\tau \, P_{t,\tau,r,pe} - E^{CCS}_{t,r} \qquad \forall t, r \tag{A.29}$$

Equation A.30: Avoided CO_2 emissions via CCS

$$E^{CCS}_{t,r} = 0.9 \sum_{pe} \lambda_{pe} \sum_{\tau} l_\tau \sum_{te \in TE^{ccs}_{pe}} G_{t,\tau,r,te} / \eta_{te} \qquad \forall t, r \tag{A.30}$$

Equation A.31: CCS constraint

$$\Delta t \sum_{t} E_{t,r}^{CCS} \leq cap_{r}^{CCScum} \qquad \forall r \tag{A.31}$$

A.7. Policy equations

Equation A.32: Target on CO_2 emission intensity of power generation

$$\frac{E_{t,r}^{CO_2}}{\sum_{\tau} l_{\tau}\, d_{t,\tau,r}} \leq \frac{E_{t_0,r}^{CO_2}}{\sum_{\tau} l_{\tau}\, d_{t_0,\tau,r}} \qquad \forall t > t_0, r \tag{A.32}$$

Equation A.33: CO_2 emission target for a group of regions

$$\sum_{r \in R^{pol}} E_{t,r}^{CO_2} \leq cap_{t}^{CO_2} \qquad \forall t \tag{A.33}$$

Equation A.34: CO_2 emission target for a single region

$$E_{t,r}^{CO_2} \leq cap_{t,r}^{CO_2} \qquad \forall t, r \tag{A.34}$$

Equation A.35: Cumulated CO_2 emission target for a group of regions

$$\Delta t \sum_{t > t_0} \sum_{r \in R^{pol}} E_{t,r}^{CO_2} \leq cap^{CO_2 cum} \tag{A.35}$$

Equation A.36: Cumulated CO_2 emission target for a single region

$$\Delta t \sum_{t > t_0} E_{t,r}^{CO_2} \leq cap_{r}^{CO_2 cum} \qquad \forall r \tag{A.36}$$

Equation A.37: National RES target

$$\sum_{\tau} l_{\tau} \sum_{te \in TE^{res}} G_{t,\tau,r,te} \geq res_{t,r} \qquad \forall t, r \tag{A.37}$$

Equation A.38: National RES target (technology specific)

$$\sum_{\tau} l_{\tau}\, G_{t,\tau,r,te} \geq res_{t,r,te} \qquad \forall t, r, te \in TE^{res} \tag{A.38}$$

Equation A.39: RES target for a group of regions

$$\sum_{r \in R^{pol}} \sum_{\tau} l_{\tau} \sum_{te \in TE^{res}} G_{t,\tau,r,te} \geq res_{t} \qquad \forall t \tag{A.39}$$

Equation A.40: RES target (technology specific) for a group of regions

$$\sum_{r \in R^{pol}} \sum_{\tau} l_\tau \, G_{t,\tau,r,te} \geq res_{t,te} \qquad \forall t, te \in TE^{res} \tag{A.40}$$

Equation A.41: Target on mimimum amount of electricity provided domestically

$$\sum_{\tau} l_\tau \sum_{te} G_{t,\tau,r,te} \geq \phi_r \sum_{\tau} l_\tau \, d_{t,\tau,r} \qquad \forall t, r \tag{A.41}$$

B. Region Codes

The region codes in this documentation are based on standard ISO 3166-1.

Table B.1: Region codes

Region code	Region name
AT	Austria
BE	Belgium
BG	Bulgaria
CZ	Czech Republic
DE	Germany
DK	Denmark
EE	Estonia
ES	Spain
FI	Finland
FR	France
GB	United Kingdom
GR	Greece
HR	Croatia
HU	Hungary
IE	Ireland
IT	Italy
LT	Lithuania
LU	Luxemburg
LV	Latvia
NL	The Netherlands
PL	Poland
PT	Portugal
RO	Romania
SE	Sweden
SI	Slovenia
SK	Slovakia
Balkan	Albania, Bosnia and Herzegovina, Kosovo, Montenegro, The former Yugoslav Republic of Macedonia, Serbia
CH	Switzerland
NO	Norway

Chapter 3

Carpe diem: A novel approach to select representative days for long-term power system modeling *

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Carpe diem: A novel approach to select representative days for long-term power system modeling

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With an increasing share of wind and solar energy in power generation, properly accounting for their temporal and spatial variability becomes ever more important in power system modeling. To this end, a high temporal resolution is desirable but due to computational restrictions rarely feasible in long-term models that span several decades. Therefore many of these models only include a small number of representative "time slices" that aggregate periods with similar load and renewable electricity generation levels. The deliberate selection of the time slices to consider in a model is vital, as an inadequate choice may significantly distort the model outcome. However, established selection methods are only based on demand variations and are not applicable to input data with a large number of fluctuating time series, which is a drawback for models with high shares of renewable energy. In this paper, we present and validate a novel and computational efficient time slice approach that is readily applicable to input data for all kinds of power system models. We illustratively determine representative days for the long-term model LIMES-EU and show that a small number of model days developed in this way is sufficient to reflect the characteristic fluctuations of the input data.

Highlights:

- We present a novel approach to efficiently cover wind & solar variability in models
- It allows simultaneously accounting for multiple variable energy sources & regions
- We validate our approach and apply it to the long-term power system model LIMES-EU
- The developed method is readily applicable to other power system models

Abbreviations: CC – combined cycle; CCS – carbon capture and storage; CSP – concentrated solar power; GT – gas turbine; LDC – load duration curve; PV – photovoltaic; RMSE – root mean square error; SSE – sum of squared errors; VRE – variable renewable energy

1. Introduction

Decarbonizing today's power systems is essential to achieve the reduction of greenhouse gas emissions required for climate change mitigation in the coming decades; the use of renewable energy sources is likely to play a key role in this context [1].[1] In order to explore future power system scenarios, different kinds of numerical models have been established. These tools serve to study possible developments of future electricity systems from a techno-economic perspective on a regional, national or international scale. Scenarios of technically feasible and economically sensible pathways provide policymakers with information needed to identify robust policy targets.

Long-term models with endogenous investments are computationally demanding, especially when optimizing intertemporally, i.e. when investment decisions are optimized simultaneously for multiple time steps. Therefore, they usually require a reduction of complexity with regard to their temporal, geographical and technical resolution. Political borders and engineering logic provide helpful guidelines for geographical and technical resolution, but the situation is less obvious for the reduction of temporal complexity. Intertemporal models spanning several decades usually optimize investment decisions for time steps of five to ten years. For modeling dispatch decisions however, a much higher temporal resolution is necessary. In order to reconcile this requirement with the computational limitations of numerical solvers, a convenient approach is to optimize the operation of generation, storage and transmission technologies for a limited number of representative situations within the year [3]. These are known as time slices. While most real-world electricity markets have an hourly – or even higher – resolution and (sub-)hourly model analysis becomes increasingly important with higher shares of variable renewable energy (VRE) in order to account for flexibility requirements, the number of time slices per year is below 100 in many long-term power system models.

The problem is, that it is not obvious which time slices should be selected from historical data to be used in a power system model and how to decide whether the selection is appropriate. For instance, a model with 20 regions and region specific time series of electricity demand, wind power infeed and solar power infeed comprises 60 time series in total. As our literature review in Section 2 shows, most established selection methods are only based on demand variations and are not applicable to input data with a large number of fluctuating time series, which is a drawback for models with high VRE shares. In plus, time slice approaches are rarely documented in detail in the description of power system models. As the way how demand and VRE fluctuations are represented in a model potentially has a strong impact on its results, a structured and reproducible algorithm suitable for a large number of fluctuating time series is needed. The aim of this paper is to close this important gap in the literature.

In this paper we present a novel approach for deriving time slices to be used as input data for long-term power system models. Our automated and reproducible approach is designed to optimally fulfil three essential requirements, i.e. the derived time slices should sufficiently reflect:

[1] See [2] for the European context.

- the annual electricity demand and average VRE capacity factors for each region,
- the region specific load duration curves of electricity demand and VRE technologies, and
- the spatial and temporal correlation of electricity demand and VRE electricity infeed.

The first requirement ensures that the quality of a region with respect to solar and wind power is correctly reflected. By replicating both common and rare situations of load and VRE infeed, as well as their respective frequency of occurrence (second requirement), the time slices neither overestimate nor underestimate single events. This serves to correctly value both base and peak load plants. The third requirement ensures that the characteristics of an interconnected multi-regional electricity system are correctly assessed and features such as large-area pooling and geographic smoothing are taken into account.

Our approach is based on Ward's [4] hierarchical clustering algorithm. We apply this algorithm on historical electricity demand and weather data to group together days with similar diurnal patterns of demand and VRE infeed. Each group of similar days is then used to define a single representative day in the power system model. In this paper, the approach is tailored to apply to input data for LIMES-EU, a long-term model for the European electricity system with several model regions and multiple VRE and demand time series per region [5]. However, due to its generic design, our method will be applicable to all kinds of power system models with multiple fluctuating time series, i.e. models with multiple VRE technologies and/or multiple regions. While we aim to select representative *days* with a given number of diurnal time slices, the approach can also be applied for selecting separate representative time slices or other groups of consecutive time slices.

The remainder of the paper is structured as follows: The following section presents a literature review of existing approaches together with their strengths and shortcomings. Section 3 describes our novel time slice approach, which we apply to historical European weather and electricity demand data in Section 4. Alongside this illustrative demonstration of the method we run a validation exercise based on a set of error metrics. In Section 5 we evaluate how many time slices are needed for the LIMES-EU model when applying our approach. In addition we discuss selected results both from the time slice approach and from LIMES-EU to address two central questions when aggregating time series to time slices: (i) the merits of seasonal differentiation and (ii) the use of representative weeks instead of days for electricity system models. Section 6 summarizes and concludes.

2. Literature review

Before variable renewable energy sources, such as wind and solar, were introduced into power systems, fluctuations in demand were the major drivers of variability in the system. Hence the traditional method for developing time slices is based purely on demand fluctuation, e. g. between day and night, between working-days and week-ends and between different seasons. Table 1 gives an overview of models that have been used in recent studies and follow this method. The models vary considerably in the number of time slices employed.

Nicolosi [6] and Kannan and Turton [7] discuss the variations in their model results when applying different numbers of representative days per season and different diurnal resolution. They find that a strong reduction in time slices leads to an underestimate of variability and thus an overvaluation of base load plants. Both Nicolosi [6] and Kannan and Turton [7] emphasize the importance of representing the fluctuating availability of VRE resources in the model's time slices in scenarios with a high share of VRE technologies; ignoring this fundamental characteristic would result in biased model results. As wind and solar power gain importance in many electricity systems [1], a number of alternative time slice approaches are being developed that go beyond the demand-based approach of the studies mentioned in Table 1 in order to better account for the fluctuations of VRE. These approaches are typically more complex than those based on average demand levels over a given time period; making an appropriate documentation and validation ever more important.

Table 1: Models with time slices that are mainly based on demand-side patterns and use averaged VRE-infeed with seasonal and diurnal fluctuations

Model	Region	Applied in	No. of time slices	No. of seasons per year	No. of days per season	No. of time slices per day
MARKAL	*various (regional/global)*	Loulou et al. [8]	6	3	1	2
DIMENSION	Europe	Fürsch et al. [9]	24	4	1	6
TIMES	Azores (Portugal)	Pina et al. [10]	288	4	3	24
TIMES	Switzerland	Kannan and Turton [7]	288	4	3	24
			8	4	1	2
TIMES	Europe	Blesl et al. [11]	12	4	1	3
ReEDS	USA	Short et al. [12], Mai et al. [13]	16+1*	4	1	4
THEA	Texas (USA)	Nicolosi [6]	288	4	3	24
			16	4	1	4

* +1 denotes the addition of a peak time slice

Table 2 presents some studies that specifically aim to represent the fluctuation patterns of VRE in their models' time slices. With the exception of Blanford and Niemeyer [14] and Sisternes and Webster [15] who approximate annual residual[2] load duration curves, all of the approaches in Table 2 follow the traditional approach by selecting a predefined number of time slices from each season.

[2] Residual load is the actual load minus VRE infeed. By design of the approach, the share of VRE in overall electricity production has to be set beforehand; the approach is therefore not suitable for models with endogenous VRE investments.

Table 2: Models with time slice approaches that specifically deal with more complex VRE fluctuation patterns

Model name	Region	Applied in	No. of time slices	Time slice specifications	Data basis
GEMS+CEEM	Germany	DENA [16]	432	4 seasons, 3 demand days and 3 wind infeed days per season, 12 time slices per day	1994-2003
DIMENSION +INTRES	Europe	Golling [17]	192	2 seasons, 8 combinations of low/high wind days over all regions, 12 time slices per day	2006-2009
DIMENSION	Europe	Nagl et al. [18]	7200	10 simulated weather years with 30 days (2 seasons) each, hourly resolution	2006-2010
US-REGEN	USA	Blanford and Niemeyer [14]	50	50 randomly selected weighted combinations of load and wind infeed	2007
LIMES-EU^{+}	Europe & MENA	Haller et al. [19]	49	4 seasons, 3 VRE situations, 4 time slices per day (plus one peak time slice)	2009
URBS-EU	Europe	Schaber et al. [20]	8064	8 years with 6 representative weeks each, hourly resolution	2000-2007
n/a	Texas (USA)	Sisternes and Webster [15]	696	4 weeks (each 7 days) with hourly resolution (plus one peak day)	2009

While Blanford and Niemeyer [14] select separate representative time slices, DENA [16], Haller et al. [19] and Golling [17] select representative days for their models. These representative days consist of a number of consecutive time slices. Sisternes and Webster [15], Schaber et al. [20] and Nagl et al. [18] also select representative groups of time slices, although each group comprises not only the time slices of one day but of several days up to one week. This allows for a better representation of flexibility requirements between days as well as for covering longer periods of low VRE infeed.

Poncelet et al. [21] present another interesting approach for selecting representative time slices, that have however not yet been applied in a power system model. The approach is based on an optimization model that aims to approximate historical Belgian duration curves of demand and electricity generation from onshore wind and photovoltaic. The benefit of an optimization model is that its objective function can be customized to the user's need, e.g. to additionally optimize the approximation of the time series' correlation. However, as the model necessarily consists of a mixed-integer problem, solving it for a large number of regions may be impossible due to its computational demand.

Despite the large variety of new time slice approaches, all approaches to date are subject to certain shortcomings: they are either based on only one VRE time series [14–17,19], are focused on only one region or disregard different spatial compositions of feed-in levels [14–16,19], or they lead to a number of time slices that is not suitable for long-term intertemporal investment models [15,18,20]. In addition, only Sisternes and Webster [15] provide a distinct validation of their approach. An efficient and reproducible approach to generate time slices based on a large number of different time series is

missing so far. The approach we present in the following section may therefore have a high value to all power system models, in particular those comprising multiple regions.

3. Novel time slice approach

The target of our time slice approach is to determine representative days in a large set of historical days, which are characterized by multiple time series of electricity demand and VRE infeed. Our approach was therefore explicitly developed in order to be applied simultaneously to a discrete number of time series. By employing a multidimensional clustering algorithm, the approximation of any load duration curve of a region's electricity demand or VRE infeed is optimized, while at the same time accounting for the simultaneous load and VRE levels of the other model regions.

The procedure is as follows: for every historical day d we create a vector V_d that incorporates all values of electricity demand and VRE infeed for every region and every time slice of that day. Thus, the number of dimensions of each vector V_d equals the number of time slices per day times the number of time series. The number of time slices per day is not part of the clustering algorithm but set exogenously beforehand.[3] The clustering algorithm groups the historical days into clusters with the objective of keeping the inner cluster variance to a minimum. From each cluster c a representative day V_c^* is derived in order to be used as input to the power system model. We choose that day $V_{d \in D_c}$ as a representative day of cluster c that is closest to the mean vector of c, which is called the 'centroid' and denoted by $\bar{V}_c$. Effectively, our time slice approach consists of the following six consecutive steps:

1. Normalizing all time series
2. Applying the clustering algorithm
3. Deriving a candidate set of clusters
4. Choosing one representative day per cluster
5. Weighting each representative day according to its cluster size
6. Scaling single time series in order to reach the correct annual average

Each step is described in detail below. As there are often many ways of pursuing a single step, we explain the reason for critical decisions where relevant.

Step 1: Normalizing all time series

The algorithm clusters the historical days based on their respective distance from each other. In order to ensure a correct evaluation of the distance between any two days, differences in wind (and solar) power infeed and electricity demand have to be measured on the same scale. We therefore normalize all time series and measure differences between load or VRE values of two days in percentage points. Demand time series are normalized according to their region specific maximum value. VRE infeed is normalized

[3] If the original time series have a higher resolution than the final representative days should have, the data first has to be aggregated accordingly.

against the maximum value achievable by the associated technology across all regions. As this value is not region specific, the time series of regions with low wind speeds (or low solar irradiance) do not achieve 100%.

A further weighting of the time series according to the importance of a technology or region is not pursued. For instance, differences in the wind power time series of Poland carry as much weight as differences in that of Luxemburg. We have chosen this approach, as assigning a higher weight to Poland's time series could lead to an underrepresentation of variability in Luxemburg's wind power time series with the effect that the electricity system model installs a non-optimal level of wind power plants in Luxemburg. As our model is used both for an aggregate analysis of the European power system and the detailed analysis of single countries, we argue that the correct representation of variability is equally important for all model regions.[4]

Step 2: Applying the clustering algorithm

A clustering algorithm groups 'similar'[5] observations into the same cluster. Hierarchical clustering algorithms start with single observations, being clusters with just one member. Then similar clusters are iteratively grouped together until only one cluster, containing all observations, remains. The number of clusters is reduced by one with each iteration. In contrast to other clustering algorithms (such as k-Means), hierarchical clustering provides the benefit of being completely reproducible: For a given input dataset, the algorithm will always lead to the same cluster structure.

We aim to minimize the deviation between historical days (observations) V_d and their representative V_c^*. V denotes a vector of diurnal load and VRE values v, with d being the index for days and c the index for clusters; D_c is the set of all days d within cluster c.

$$\min \sum_{c} \sum_{d \epsilon D_c} \|V_d - V_c^*\|^2$$

In order to group similar observations V_d into the same cluster we apply the hierarchical clustering algorithm described by Ward [4]. Ward's algorithm perfectly suits our purpose of grouping similar days as it is based on a distance measure that will eventually lead to clusters with a minimum inner-cluster variance. The distance between two observations (d_1 and d_2) is defined as the Euclidean distance $dist_{d1,d2}$.

$$dist_{d1,d2} = \|V_{d1} - V_{d2}\|$$

[4] If only aggregate results are of interest, a model might benefit from a weighted approach: in an interconnected system it would be easy to supply the electricity demand of Luxemburg from the surrounding countries and a better representation of the demand variability of larger countries could then lead to higher accuracy in the aggregated results.

[5] The definition of 'similarity' varies between different clustering algorithms. See below for the clustering algorithm by Ward [4] that we apply.

A central value in Ward's algorithm is the centroid $\bar{V}_c$ which is the mean vector of the observations V_d grouped into the same cluster ($n(D_c)$ denotes the number of days grouped into cluster c).

$$\bar{V}_c = \frac{1}{n(D_c)} \sum_{d \epsilon D_c} V_d$$

Ward's algorithm iteratively joins the two clusters whose combination results in the smallest increase in the overall sum of squared errors SSE between the observations V_d and their clusters' centroids $\bar{V}_c$. In other words, it attempts to keep the inner cluster variance to a minimum level.

$$SSE = \sum_c \sum_{d \epsilon D_c} \|V_d - \bar{V}_c\|^2$$

With each iteration the sum of squared errors increases. The increase $I_{d1,d2}$ caused by the merge of the two observations d_1 and d_2 is

$$I_{d1,d2} = \left(V_{d1} - \tfrac{1}{2}(V_{d1} + V_{d2})\right)^2 + \left(V_{d2} - \tfrac{1}{2}(V_{d1} + V_{d2})\right)^2 = \tfrac{1}{2} dist_{d1,d2}^2$$

We consequently define the distance $dist'$ between two clusters based on the resulting increase I in the overall sum of squared errors when those two clusters are merged.

$$dist' = \sqrt{2I}$$

After each merge of two clusters c_1 and c_2, we calculate the distance $dist'$ between the new cluster c_1+c_2 to an existing cluster c_3 via the Lance-Williams formula [22,23][6], where n_c denotes the number of observations in a cluster. The distances $dist'$ on the right hand side of the formula are already known from previous iteration steps.

$$dist'_{c1+c2,c3} = \frac{n_{c1}+n_{c3}}{n_{c1}+n_{c2}+n_{c3}} dist'_{c1,c3} + \frac{n_{c2}+n_{c3}}{n_{c1}+n_{c2}+n_{c3}} dist'_{c2,c3} - \frac{n_{c3}}{n_{c1}+n_{c2}+n_{c3}} dist'_{c1,c2}$$

In each iteration the two clusters with the smallest distance are merged and the number of clusters reduces by one. The algorithm is repeated until only one cluster that contains all observations is left. Fig. 1 gives a visualization of the clustering algorithm for the data presented in Section 4.

[6] See [22] for the general formula and [23] for the particular algorithm applied here.

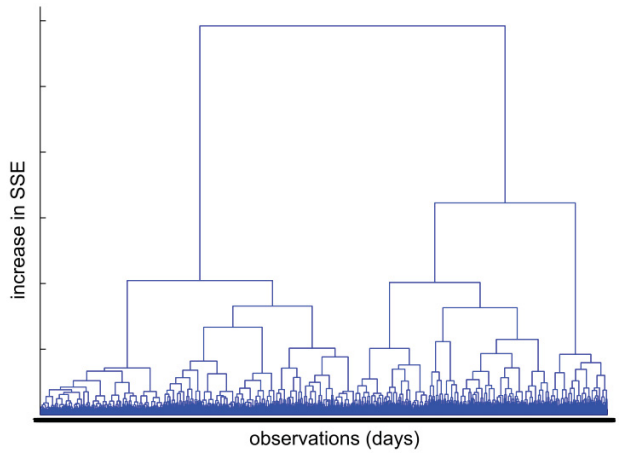

Fig. 1: Dendrogram of the clustering algorithm showing the consecutive grouping of two clusters into a joint cluster and the resulting increase in the overall sum of squared errors (SSE, y-axis). All days (x-axis) are consecutively grouped together until only one cluster is left.

Step 3: Deriving a candidate set of clusters

Instead of continuing to merge observations and clusters until only one cluster is left, one could also predefine a desired number of clusters or a threshold (e.g. for the sum of squared errors) that terminates the algorithm once it is surpassed. However, when applying the algorithm to derive representative days for a power system model, the appropriate number of clusters should not be defined before or within the algorithm. Instead, the user should run the model with different numbers of clusters in order to evaluate the trade-off between model computation time and model accuracy, as we do in Section 5.1.

After having completed the algorithm, we have information on the clusters merged in each iteration. Based on this information, we select candidate sets of clusters (each set consisting of the clusters remaining after a certain iteration step) in order to compare the results of the power system with different numbers of representative days. The following steps are separately performed for each candidate set of clusters.

Step 4: Choosing one representative day per cluster

All historical days that are grouped into the same cluster will be represented by the same representative day in the power system model. A straightforward approach would be to use the clusters' centroids $\bar{V}_c$ as representative days, as they contain the mean values of all observations in their cluster. However, in Section 4.2 we show that for our dataset the load duration curves of the various time series are better replicated when using specific historical days, rather than the clusters' centroids, as representative days. We therefore choose the day $V_{d \in D_c}$ as the representative day V_c' that is closest to the cluster's centroid $\bar{V}_c$. The distance between the historical days $V_{d \in D_c}$ and the centroid $\bar{V}_c$ is again defined by the Euclidean distance.

$$V_c' \in \arg\min_{d \in D_c} \|\bar{V}_c - V_d\|$$

Step 5: Weighting each representative day according to its cluster size

The approach accounts for typical days that reflect common load and VRE patterns for the particular electricity system, as well as for extreme days that only occasionally occur but are nevertheless important for the optimal composition of the electricity system. Extreme days are part of smaller clusters that long remain separated in the clustering algorithm (Step 2) due to their high distance to other clusters. We weight the representative days used for the power system model with a factor ω_c according to the relative size of their respective cluster which is defined by the number of historical days $n(D_c)$ that are grouped into it, and the total number of days $n(D)$ in the dataset.

$$\omega_c = \frac{n(D_c)}{n(D)}$$

In this way we account for the fact that large clusters, containing many days, represent a common load and VRE situation, while small clusters represent an occasional pattern. Approaches that do not assign different weights to their time slices[7] risk omitting extreme events and tend to use more time slices than necessary for common days with similar patterns.

Step 6: Scaling single time series in order to reach the correct annual average

The weighted average of the representative day values may deviate from the average of the underlying historical time series. To ensure correct average demand levels and capacity factors by technology and region the values $v'_{s,c,\tau}$ of each representative day V_c' are scaled as necessary (s is the index for the load and VRE time series; τ denotes the time slices per day). Scaling is performed separately for each time series. The scaling factor σ_s is derived from the relationship between historical values $v_{s,d,\tau}$ and the values $v'_{s,c,\tau}$ of the clusters' representative days. The resulting values $v^*_{s,c,\tau}$ are used as input for the power system model.

$$\sigma_s = \frac{\sum_d \sum_\tau v_{s,d,\tau}}{\sum_c \sum_\tau n(D_c)\, v'_{s,c,\tau}}$$

$$v^*_{s,c,\tau} = \sigma_s\, v'_{s,c,\tau}$$

Upscaling is pursued in a way that ensures that the normalized values $v^*_{s,c,\tau}$ of a resulting representative day V_c^* are not greater than 1. Where a value is scaled above 1, it is reset to 1 and the other values of the time series are re-scaled in order to reach the correct average.

[7] e.g. Sisternes and Webster [15] and the established demand based approaches in Table 1

4. Application of the approach to electricity demand and VRE time series

We apply our time slice approach to produce input data for the European electricity system model LIMES-EU. This procedure is independent of the actual characteristics of the power system model. Therefore, we concentrate on the characteristics of the input data in this section, while the description of the model is covered in Section 5 together with its application. After presenting the data, we perform the six steps of our time slice approach in Section 4.1 and validate the resulting clusters in Section 4.2.

The power system model LIMES-EU requires several input parameters with time(-slice)-dependent values for each model region: electricity demand and fluctuating infeed from the VRE technologies of onshore wind, offshore wind, photovoltaic (PV) and concentrated solar power (CSP). In order to account for the fact that wind speeds and solar radiation not only vary *between* but also *within* the model regions, we consider three time series for each model region and VRE technology in LIMES-EU.[8]

We use ENTSO-E [24] data for the historical electricity demand levels and historical weather data from ECMWF [25] for the VRE infeed. Using weather data rather than historical infeed data allows us to take a longer time span into consideration which prevents unusual years being overestimated. The ECMWF dataset comprises 33 years of global solar radiation, ground temperature and wind speed levels at a height of 120m for Europe. For every third hour between 1979 and 2011 information is provided for local data points in a spatial resolution of 0.75°x0.75°.[9] After converting this weather information into time series of infeed levels of representative wind and solar power plants, the data points are aggregated to replicate the VRE infeed in the model's sub-regions[10].

Intra-year demand fluctuations follow distinct diurnal, intra-week and seasonal patterns. Though the absolute demand levels change across the years due to demographic and economic reasons, the relative intra-year fluctuations are assumed to remain the same. The hourly demand data of 2010 and 2011 available from ENTSO-E [24] for all model regions is therefore deemed to be representative for the *intra*-year demand fluctuations between 1979 and 2011. Future *inter*-year growth of annual demand is subject to scenario assumptions. However, as we use normalized values for the clustering, these scenario assumptions do not affect the time slice approach.

[8] The first sub-region covers the 10% best wind sites (or solar sites respectively), the second sub-region covers the following 30% wind (solar) sites and the third sub-region comprises the 60% of a model region's wind (solar) potential with the lowest wind speeds (solar radiation).
[9] 0.75° represent 83.4km in north-south distance and about 40-60km in west-east distance (depending on the latitude).
[10] see Nahmmacher et al. [5] for more details

4.1. Deriving time slices from the time series

Each observation considered in the clustering algorithm contains information on the different coincident load and VRE levels of every region. 29 model regions and 13[11] time series per region result in a total of 377 time series. In order to cluster similar days, each observation has a scope of one day, i.e. each observation contains multiple values per time series, rather than only one. With eight time slices per day this leads to a total of 3016 values per observation. The number of observations amounts to 12053 over the period from 1979 to 2011.

Before starting the clustering algorithm, each time series is normalized to its maximum value (cf. Step 1). While solar and wind infeed expand virtually over the whole range between 0 and 100%, none of the normalized electricity demand time series has a situation with less than 30% of peak demand. Consequently, the range of normalized demand fluctuations is much smaller compared to the time series of wind and solar infeed, which possibly results in its underestimation in the clustering algorithm. However, it turns out that fluctuations in demand are properly covered by our approach.

In fact, the representative days' load duration curves of the demand and solar time series quickly converge to the original load duration curve. Just two representative days cover the characteristic fluctuations of these time series fairly well. This is because most fluctuations in demand and solar radiation are based on differences between day and night – and the day-night shift is already covered when clustering whole days instead of single time slices.

Fig. 2a-c show the original load duration curves of onshore wind, solar PV and electricity demand in Germany together with approximations based on different numbers of representative days. The load duration curves of the representative days are constructed in a way that accounts for the relative weight of a representative day (cf. Step 5). It can be seen that a higher number of representative days leads to a more accurate replication of the original load duration curve. The load duration curve of wind power is the most challenging to replicate as wind levels do not follow a distinct diurnal pattern and fluctuate substantially between days. In addition to the visual validation of the time slice approach given by Fig. 2a-c, the following section provides a numerical discussion of the accuracy of the approximation.

[11] For each region, the observations contain data about the electricity demand and the infeed of four VRE-technologies in three different resource grades per region, leading to 13 time series per region.

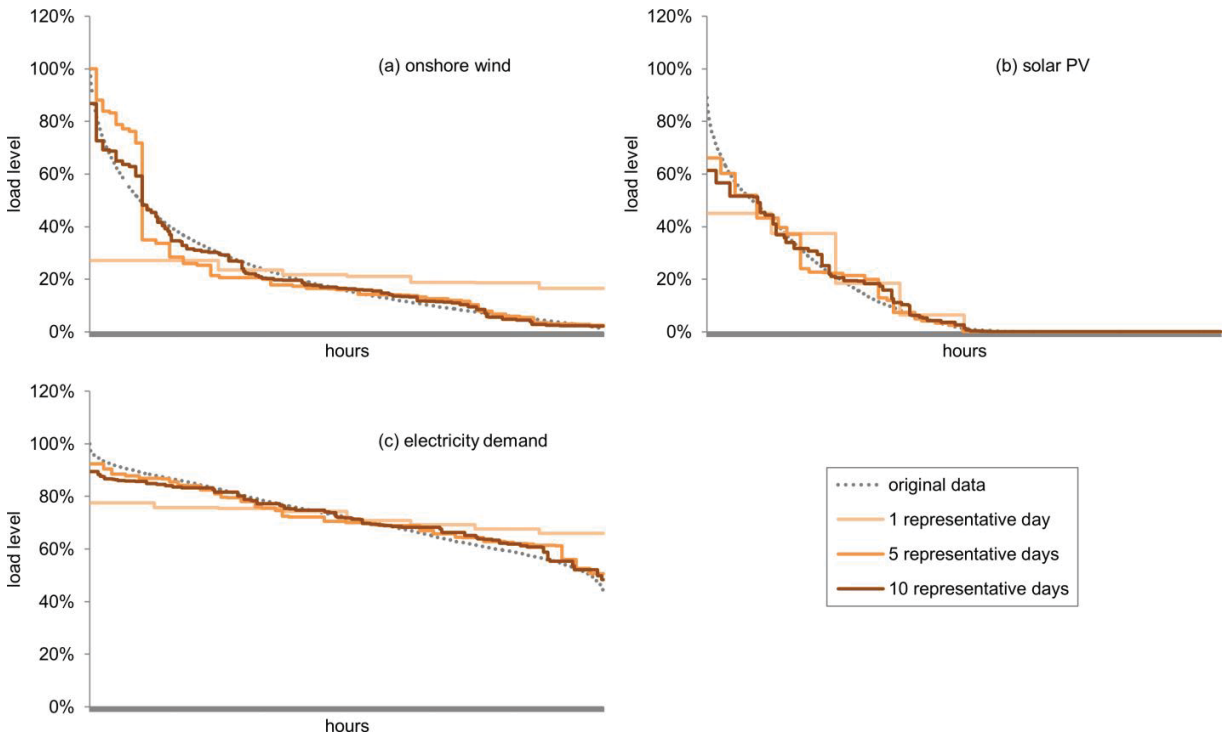

Fig. 2: Approximation of Germany's load duration curves for (a) onshore wind, (b) solar PV and (c) electricity demand, displaying original data and results for one, five and ten representative days.

4.2. Accuracy of the approximation

To measure the accuracy of the approximation with varying numbers of representative days, we use a set of three different error metrics, namely (1) the average root mean square error (RMSE) between the values of the original time series and their representatives, (2) the representation of the time series variability and (3) the representation the correlation between time series. Together they show that: (i) a higher number of representative days leads to a better replication of historical values and (ii) using an actual observation as a representative day yields a better approximation than using the clusters' centroids.

In the following, we analyze four different RMSEs that reflect the deviation between historical days and their corresponding values resulting from the clustering algorithm. These corresponding values differ between the four indicators (see Table 3 for an overview): $RMSE(\bar{V})$ represents the deviation between the historical days and their clusters' centroids. It is directly derived from the clustering algorithm's objective function – the overall sum of squared errors (SSE) between historical days and the centroids of their clusters. $RMSE(V^*)$ represents the deviation between the historical days and the historical day that is closest to their clusters' centroid. As described in Step 4 of the time slice approach, we use these historical days as representative days for the power system model.

Analogous to the first two indicators $RMSE(\bar{V}_{LDC})$ and $RMSE(V^*_{LDC})$ refer to the average deviation between the load duration curves consisting of historical values, and the load duration curve consisting of their corresponding values (i. e. the clusters' centroids or the historical days that are closest to the clusters' centroids, respectively). A formal description of the RMSEs is provided in the Appendix.

Table 3: Overview of the indicators for measuring the accuracy of the approximation

Indicator	Description
$RMSE(\bar{V})$	RMSE between the historical values and the values of their cluster's centroid (averaged over all time series)
$RMSE(V^*)$	RMSE between the historical values and the values of their cluster's representative day (averaged over all time series)
$RMSE(\bar{V}_{LDC})$	RMSE between the load duration curves consisting of historical values and the load duration curves consisting of the clusters' centroid values (averaged over all time series)
$RMSE(V^*_{LDC})$	RMSE between the load duration curves consisting of historical values and the load duration curves consisting of the clusters' representative day values (averaged over all time series)

Note: RMSE – Root Mean Square Error; LDC – Load Duration Curve

Fig. 3 shows the values[12] for these indicators depending on the number of clusters. As prescribed by the design of the clustering algorithm, the root mean square error $RMSE(\bar{V})$ between the observations and their respective clusters' centroids decreases with an increasing number of clusters. If each observation had its own cluster, the indicator (and all others) would be zero. It is also obvious that $RMSE(V^*)$ has to be higher than $RMSE(\bar{V})$: the sum of distances between all observations of one cluster and the centroid of this cluster is necessarily smaller than the sum of distances to another specific observation of the cluster.

However, our data shows that the load duration curves of the time series are better replicated by the load duration curves of the historical days closest to the clusters' centroids than by the load duration curves of the clusters' centroids themselves: $RMSE(V^*_{LDC})$ is lower than $RMSE(\bar{V}_{LDC})$. As Fig. 4 shows illustratively, the selected historical days better replicate the extreme values at the upper and lower end of the load duration curve.

[12] The exact values are given in the Appendix.

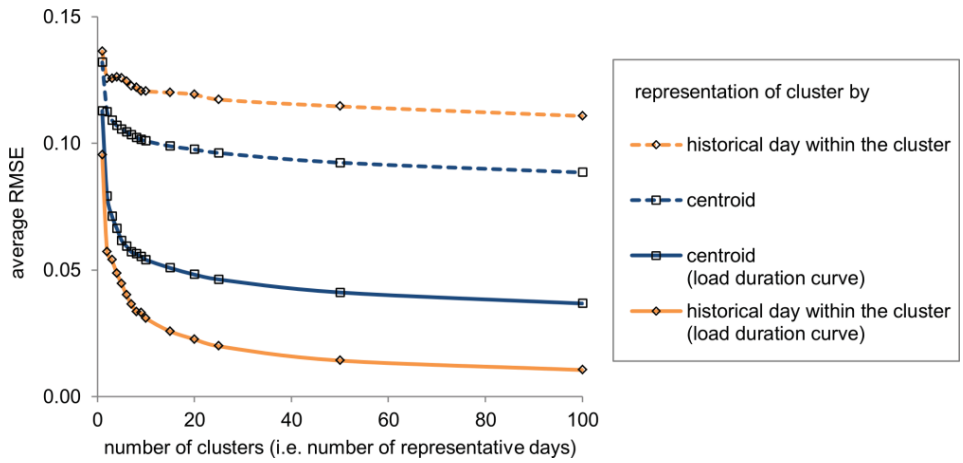

Fig. 3: Increasing approximation accuracy with an increasing number of clusters based on the RMSEs. The use of the historical days that are closest to the clusters' centroids (solid orange line) yields a better approximation of the load duration curves than the use of the clusters' centroids (solid blue line).

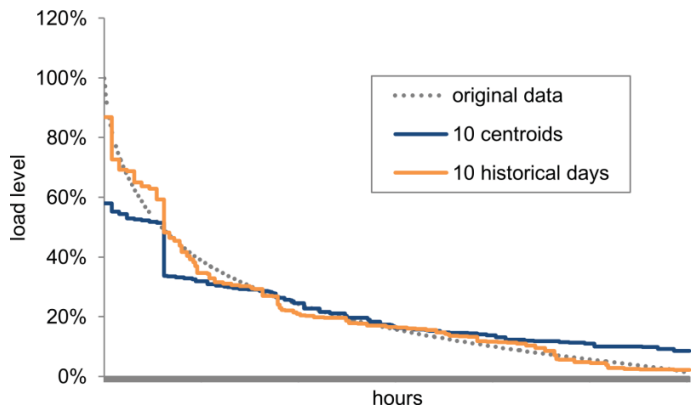

Fig. 4: Approximation of Germany's onshore wind load duration curve, showing the load duration curve of the original data together with two load duration curves resulting from 10 clusters – one consisting of the clusters' centroids, the other consisting of the historical days that are closest to the clusters' centroids.

The other two error metrics support the finding that the historical days closest to the clusters' centroids are more suitable to be used in a power system model than the centroids themselves: In addition to measuring the accuracy of the approximation based on RMSEs, we also test for the covered variability per time series (as in Ludig et al. [26]) and for the representation of the correlation between the time series (as in Poncelet et al. [21]). The covered variability $VarC$ reports the share of a series' variance $var(V_s)$ that is represented in the respective representative series. A value of 1 indicates a perfect representation of the original time series' variability. The following equation shows the calculation for the variability covered by the historical days V^* chosen as representative days; the calculation of the variability covered by the clusters' centroids $\bar{V}$ is done correspondingly.

$$VarC(V^*) = \frac{var(V_s^*)}{var(V_s)}$$

The representation of the correlation between time series (i.e. between regions but also between e.g. wind power and demand in one region) is reflected by the difference in the correlation values of the original time series to the correlation values of the time slices. The correlation $corr$ between two time series s_1 and s_2 may have a value between -1 and +1. Consequently, the difference in the correlation (i.e. the correlation error $CorrE$) between an original time series and its representative one may vary between 0 and 2; with 0 indicating a perfect representation of the correlation between the two time series. The following equation shows the calculation of the correlation error for the historical days V^* chosen as representative days; the calculation of the correlation error for the clusters' centroids $\bar{V}$ is done correspondingly.

$$CorrE(V_{s1}^*, V_{s2}^*) = |corr(V_{s1}^*, V_{s2}^*) - corr(V_{s1}, V_{s2})|$$

When using actual observations as representative days, both the average covered variability $VarC$ and the average correlation error $CorrE$ converge rapidly towards their target values (1 and 0, respectively) when increasing the number of representative days, as Fig. 5 shows. In comparison, the clusters' centroids attain significantly weaker values for the average covered variability and the average representation of the time series' correlations. For this reason we propose to use real observations as representative days for the power system model rather than the centroids of the clusters (cf. Step 4).

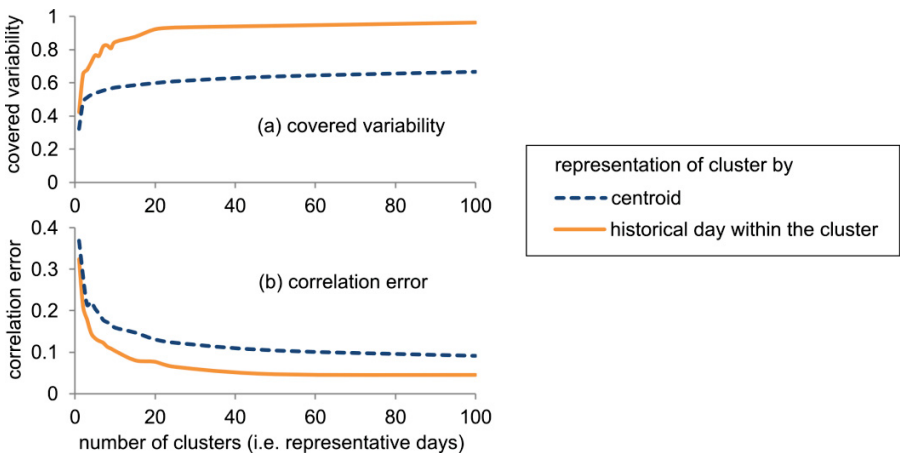

Fig. 5: Increasing covered variability (a) and decreasing correlation error (b) with increasing number of clusters. The use of the historical days that are closest to the clusters' centroids (solid orange lines) yields a better approximation of the time series' variability and correlation than the use of the clusters' centroids (dashed blue lines).

5. Testing the representative days with the power system model LIMES-EU

We use the representative days generated with our time slice approach in the previous section as input for LIMES-EU [5] in order to answer the following questions:

1. How many representative days are required to appropriately cover the variability of load and VRE infeed (Section 5.1)?
2. How reasonable is a seasonal differentiation in time slice approaches, i. e. selecting of representative days for each season separately (Section 5.2)?
3. What are the merits and drawbacks of modeling representative days rather than representative groups of consecutive days, such as weeks (Section 5.3)?

LIMES-EU (the Long-term Investment Model for the Electricity System of the European Union) was originally published in an earlier version LIMES-EU$^+$ by Haller et al. [19]. It is a linear model developed for determining cost-optimal investment pathways for the European power system. Starting with the installed capacities of 2010 it simultaneously optimizes dispatch and investment decisions for generation, storage and international transmission technologies for every fifth year until 2050. This simultaneous, intertemporal optimization of the investment pathway from 2010 to 2050 is computationally demanding. However, it is necessary in order to explore how long-term targets such as the 2050 CO_2 emission reductions envisaged by the EU Commission affect the optimal investment pathway and technology choice in previous years. Nahmmacher et al. [5] provide a detailed documentation of the model LIMES-EU.

The optimal intra-annual dispatch is calculated for a limited number of time slices. Emissions and costs for producing electricity in these time slices are scaled up according to a predefined weighting and totaled annually. The weighting may differ between time slices.

In its current version the model comprises 26 of the 28 EU Member States[13] plus Norway, Switzerland and the Balkan region. The capacities of generation and storage technologies are aggregated at national level, with each country constituting one model region[14]. The international transmission grid in LIMES-EU is represented by Net Transfer Capacities (NTCs) between the model regions.

For the applications in this paper we set an exogenous CO_2 reduction target for the power sector of minus 95% up to 2050 in comparison to 1990. The reduction pathway between 2010 and 2050 describes a linear increase. Other policy constraints are kept to a minimum, e.g. there are no additional policies implemented to foster the electricity production from renewable energy sources. The use of primary energy sources is subject to environmental and/or societal constraints [5]. In order to reflect the political situation of nuclear power in Europe, we assume a nuclear phase-out in Germany, Belgium and Switzerland. New installations in other countries are limited to those currently under construction or planned, and for replacing depreciated capacities.

[13] The insular states Malta and Cyprus are not included in the current model version
[14] with the exception of the non-EU countries in the Balkan region that are grouped to one model region

5.1. Appropriate number of representative days

In order to evaluate the approach and determine the number of representative days[15] to use in the intertemporal model LIMES-EU, we test different numbers of time slices in a non-intertemporal version of the model with the same geographical scope and the same objective function. This version of LIMES-EU is less computationally demanding and thus capable of solving with a considerably higher temporal resolution. Like the intertemporal model, it minimizes overall system costs according to the electricity demand in the different regions. However, the model is only solved for one year, annualizing the investment costs. Parameters such as investment costs and the CO_2 reduction target are based on assumptions for the year 2050 [5]. To give the model as much freedom as possible it does not build on historical assets, i.e. the model is solved in a so-called 'greenfield' version optimizing the total power system.

We compare the outcomes of model runs with different numbers of time slices ranging from 1 to 100 representative days (i.e. 8 to 800 time slices). As Fig. 6 shows, the share of VRE is up to 16 percentage points higher in the model runs with only very few representative days. This is due to the fact that the fluctuations of VRE are represented to a much lesser extent in these runs. This overestimation of the system value of VRE eventually leads to an underestimate of the total system cost: the model run with only one representative day results in 13% lower overall cost than the model run with 100 representative days.

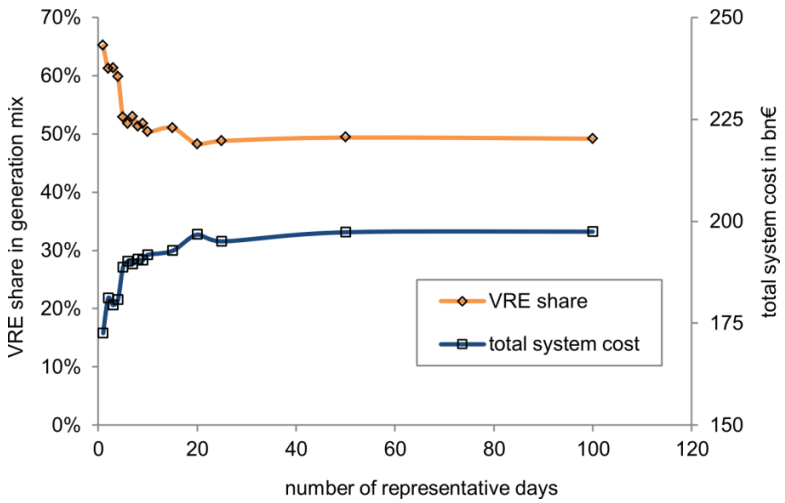

Fig. 6: Total system cost (in bn€) and share of variable renewable energy (VRE) in the electricity generation mix depending on the number of representative days used in the greenfield version of LIMES-EU.

[15] The number of time slices within each representative day is predefined and not part of the analysis. The weather data from ECMWF [25] is given in three-hourly resolution. We deem this sufficient to cover the characteristic diurnal demand and VRE fluctuations and consequently use eight time slices per day with a length of three hours each (see Ludig et al. [26] for a comparison of model results with different numbers of diurnal time-slices).

The more time slices we use in the model, the more the results resemble the outcome of the run with 100 representative days. However, this convergence is not monotonic; e.g. the total system costs of the run with 20 representative days are higher than the costs of the neighboring runs with 15 and 25 days respectively (cf. Fig. 6). This is due to the fact that, rather than using average values (i.e. centroids), we use observed days to represent the days grouped into the same cluster.[16] Extreme values such as peak demand or peak wind power infeed are therefore not necessarily more pronounced in a set of more representative days. However, the resulting distortions are only minor and the notion that a higher number of time slices leads to a more accurate representation of variability and costs undoubtedly holds true.

Fig. 7 provides more detailed information on the cost-efficient electricity mix found by the different model runs. While biomass and hydro power are always used to their maximum potential, the third carbon neutral and dispatchable technology – nuclear power – is virtually non-existent in the model run with only one representative day. However, its share increases to 19% in the electricity mix with 100 representative days. In contrast, the optimal electricity generation of variable wind power is 30% higher when modeling only one instead of 100 representative days. Wind power is favored in a model with low temporal resolution and a weak representation of its variability, because its levelized cost of electricity (LCOE) is lower than the LCOE of nuclear power. With higher temporal resolution the value of VRE decreases, which leads to a higher deployment of the more costly but to a certain extent dispatchable nuclear power.

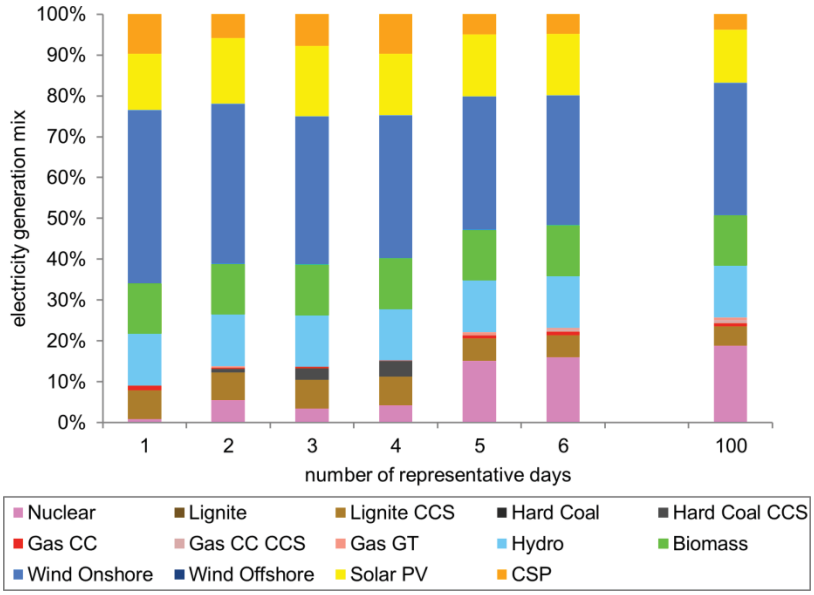

Fig. 7: Electricity generation mix depending on the number of representative days used in the greenfield version of LIMES-EU *(CC: combined cycle; CCS: carbon capture and storage; CSP: concentrated solar power; GT: gas turbine; PV: photovoltaic).*

[16] cf. Step 4 of the time slice approach (Section 3) as well as Section 4.2

In addition to nuclear power, the share of gas turbines in the capacity mix rises considerably: from 0% with one representative day to 5% with 100 representative days. However, despite their significant share in the capacity mix gas turbines contribute only 0.6% to the electricity generation mix. As they are the most flexible and least capital-intensive thermal power plants, they are installed to provide electricity in situations of low VRE infeed, but remain idle most of the time. As maximum emissions are fixed, the high CO_2 intensity of gas turbines leads to an overall decrease in electricity production from fossil fuel power plants.

In short, one representative day is obviously not enough to sufficiently cover the fluctuations of electricity demand and VRE electricity production. The most accurate results are obtained by including as many representative days as possible in the model. However, in practice the appropriate number of time slices has to be found by trading between computation time and accuracy. Based on Fig. 6 and Fig. 7 we find that in our case, 48 time slices (six representative days) are sufficient to obtain results that closely approximate the results with 800 time slices. The share of VRE in the electricity mix differs by just 2.5% between the model run with 100 representative days and the model run with six representative days. The difference in total system costs between the two runs is 4%. To obtain more accuracy the temporal resolution would have to be substantially increased. However, given that computation time increases disproportionately, we deem the accuracy obtainable with 48 time slices to be sufficient.

5.2. Analysis of resulting clusters with regard to seasons

Most conventional time slice approaches derive their time specific model input data by selecting (criteria-based or randomly) a predefined number of hours, days or weeks from each season of the year. The number of hours, days or weeks to select is equal for each season. In this section we analyze the clusters generated by our approach with regard to their seasonal composition. In its default version, the approach does not specifically consider seasons when clustering historical days.

Based on the input data used, the compulsory differentiation of seasons would lead to a higher number of necessary clusters. Requiring an equal number of clusters for each season causes the mean square error (cf. Section 4.2) to be 8% higher for the selection of 2 clusters, and 7% higher when selecting 3 clusters per season (compared to 8 and 12 chosen clusters without such restrictions). Naturally, the approximation accuracy would decrease further if the representative days had to be chosen in order to carry the same weight in the model.

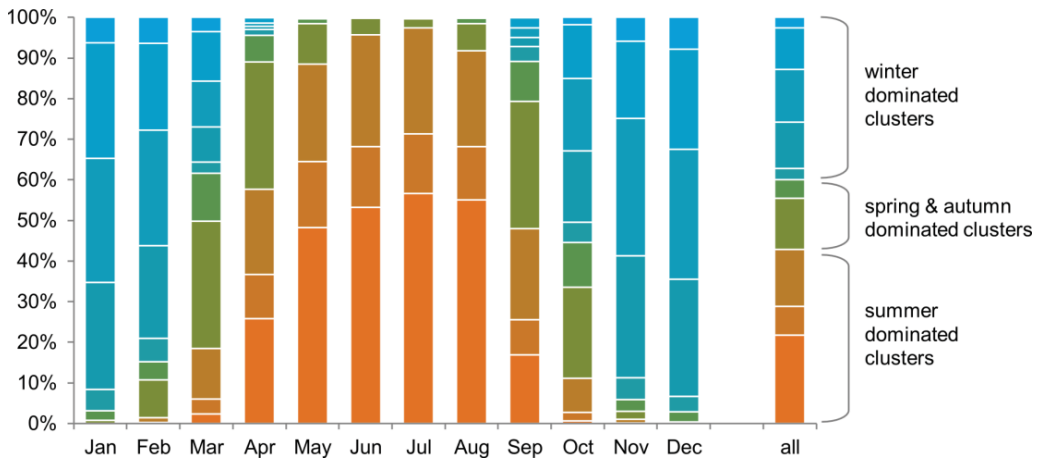

Fig. 8: Distribution of historical days (sorted by months) to 10 clusters, e.g. 57% of the 990 July days from 1979 to 2011 are grouped to cluster #1 (bright orange).

For the case of ten clusters, Fig. 8 shows how the historical days (sorted by months) that are used in this paper are distributed among the clusters obtained with the time slice approach. It suggests two reasons why it is not useful to use the same number of representative days from each season when aiming to minimize the number of necessary representative days: (i) spring and autumn days are fairly similar with regard to our input data, they are grouped into the same clusters; (ii) there is a higher variance over winter days than summer days, so fewer clusters are needed for summer.

Five of the ten clusters are dominated by winter days (blue in Fig. 8) while three are dominated by summer days (orange). More than 90% of the days from May to August are covered by the three summer clusters and four clusters cover 99% of all summer days. Spring and autumn together dominate only two clusters (greenish in Fig. 8), while many of their days fit well into clusters dominated by winter or summer days. This suggests that load and VRE patterns are more stable in summer and more variable in spring and autumn; however, they do not differ much between those two transition seasons. Time slice approaches that select the same number of representative days from each season do not account for these patterns and result, *ceteris paribus,* in a less accurate representation of the overall load and VRE infeed structure (cf. also Sisternes and Webster [15]).

Note that the seasonal approach might be less questionable with input data for other models. For example, the seasonally changing availability of water from glaciers may be important for models with high shares of hydro power. In such a case, time series for water levels and precipitation could be added to the input data for the time slice approach. A distinct seasonal differentiation in the algorithm used is still not required, as including such time series should automatically result in clusters that reflect the seasonal differences of the hydro time series.

5.3. Using representative days instead of representative weeks

While the above approach derives representative days, other recent time slice approaches derive representative groups of consecutive days to be used in power system models. Nagl et al. [18] derive groups of three days; Sisternes and Webster [15] and Schaber et al. [20] even use weeks. Modeling consecutive days allows for a better representation of different interday[17] storage needs and technology options: In LIMES-EU we cannot distinguish whether an interday storage system is charged and discharged several times per year in order to shift electricity between nearby days or whether it is charged during one season and discharged during another. While, for the first case, established short-term storage options such as pumped-hydro may be used, the second application calls for less efficient and more expensive long-term storage options such as power-to-gas. An assessment of different interday storage options is only possible when implementing consecutive days.

In turn, the use of representative groups of consecutive days results in more time slices that are rather similar to each other. In our time slice approach such days would be grouped into one cluster. As the overall number of time slices is limited by computational restrictions, more similar days caused by the consecutive-day-approach translates to less space for other characteristic days that are important when determining the optimal structure of the power system.

Ultimately, the decision whether to select single days or representative groups of days depends on the research question and the model in use. Despite the higher computational cost, the advantages of consecutive days should be particularly considered for long-term models with a focus on different storage options. Our time slice approach is easily modifiable for selecting groups of representative consecutive hours spanning more than one day.

For the case of LIMES-EU we favor computation time and an optimal representation of VRE variability over the accurate representation of interday storage. With separate representative days, the required capacity of an interday storage system can only be analyzed in terms of possible power input and output, not in terms of storage size. In order to not overestimate the potential role of interday storage, efficiency and installation costs are based on long-term storages such as power-to-gas rather than less expensive and more efficient short-term to medium-term storage technologies such as pumped-hydro.

Fig. 9 shows a typical generation pattern retrieved from the intertemporal version of LIMES-EU aggregated over all model regions for 2050. Of the two implemented storage options – intraday and interday – only intraday storage is installed in significant amounts. The assumed techno-economic characteristics for interday storage result in low deployment of this storage option. Instead of interday storage, conventional generation capacities are used to secure sufficient power supply during days of low VRE infeed. Given the modeling assumptions, the results from LIMES-EU should be interpreted as a lower limit for the cost-efficient deployment of interday storage. A more detailed analysis of different

[17] *Inter*day storage is used to shift electricity supply between different model days. In contrast, *intra*day storage is used to level out excess and deficit of power supply between time slices of the same day.

interday storage options in scenarios generated by LIMES-EU is desirable for further research, but beyond the scope of this paper.

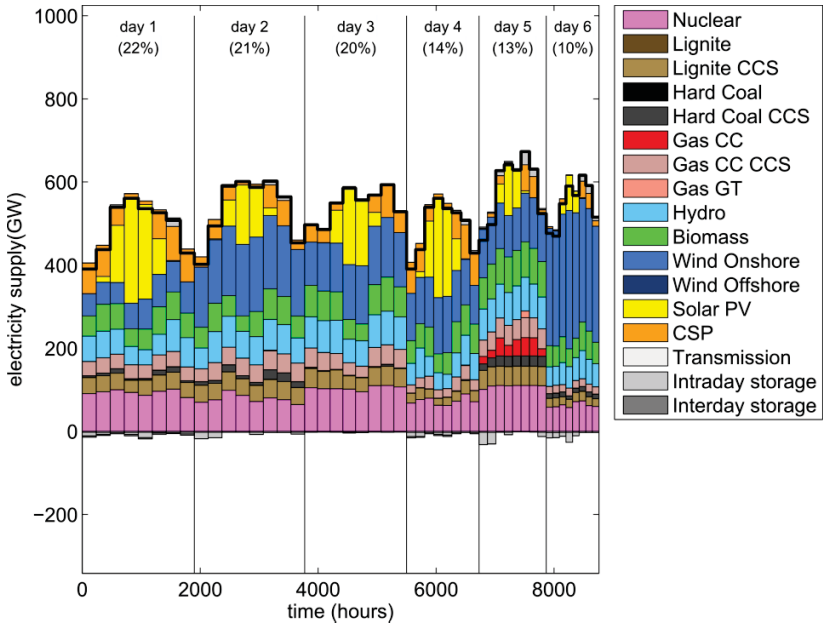

Fig. 9: Electricity generation mix and demand for 48 time slices in the year 2050, aggregated over Europe *(CC: combined cycle; CCS: carbon capture and storage; CSP: concentrated solar power; GT: gas turbine; PV: photovoltaic).*

6. Conclusion

We presented a novel approach to derive and select representative days as input data for power system models. As is the case for other time slice approaches, the intended aim of our method is to keep computational requirements for the model to a minimum, by decreasing temporal resolution, while still ensuring reliable results. Whereas most other approaches tend to account for only one time series (e.g. electricity demand in one region), we are able to apply our method to multidimensional input data. Thereby we can optimize the replication of variability of multiple time series, e.g. electricity demand data and multiple VRE electricity production data for multiple model regions. This is especially important considering that electricity production from VRE is expected to play a dominant role in future power systems required to achieve ambitious climate mitigation goals.

At the core of our method is the hierarchical clustering algorithm described by Ward [4]. By its design, our method can be easily transferred to input data for different kinds of power system models. It is neither restricted to certain technologies or geographical regions nor to determining representative days rather than representative hours or representative groups of days. In order to make our approach effectively applicable for other models, we provide a comprehensive and transparent documentation

and validate the resulting time slices with different error metrics and an illustrative application in a power system model.

We applied the method on input data for the long-term European electricity system model LIMES-EU. The input data consists of the time series for electricity demand as well as wind and solar power infeed for 29 model regions. We show that under a very low temporal resolution, the variability of VRE is not sufficiently covered. This results in an overestimate of the share of VRE in the electricity system and an underestimate of dispatchable generation technologies such as gas turbines and nuclear power plants. Total system costs are also incorrectly captured when not taking into account the full variability of demand and VRE. However, we show that with our time slice approach, 48 time slices (i.e. six representative days) are sufficient to obtain model results that are very similar to those obtained with a much higher temporal resolution.

We argue that for our input data a seasonal differentiation, as applied by many other time slice approaches, is not useful in order to keep the necessary number of time slices to a minimum. The use of representative weeks instead of representative days also increases the number of necessary time slices but may be required when the power system model shows high shifts of electricity provision between model days via storages. In the case of LIMES-EU; however, we show that the use of representative days is reasonable.

In summary, this generic and customizable approach allows researchers involved in power system modeling to improve the representation of VRE variability in their models. Correctly covering VRE variability is an absolute necessity in order to deliver reliable scenarios and to provide sound policy advice.

Acknowledgements

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Appendix

$RMSE(\bar{V})$ denotes the average root mean square error per time series between historical values $v_{s,d,\tau}$ and the values of their corresponding cluster's centroid $\bar{v}_{s,c,\tau}$. The indices used here are s for time series, d for days, c for clusters and τ for diurnal time slices. $n(S)$ denotes the number of time series, $n(D)$ the number of days and $n(T)$ the number of time slices per day.

$$RMSE(\bar{V}) = \frac{1}{n(S)} \sum_{s} \sqrt{\frac{1}{n(D)n(T)} \sum_{c} \sum_{d \epsilon D_c} \sum_{\tau} \left(v_{s,d,\tau} - \bar{v}_{s,c,\tau}\right)^2}$$

$RMSE(\bar{V}_{LDC})$ denotes the average root mean square error between the load duration curves of historical values $v_{s,i}$ and the load duration curves consisting of the values of their corresponding clusters' centroids $\bar{v}_{s,i}$. i denotes the position of a value in the load duration curve. To construct the load duration curve of the centroid values, the occurrence of each centroid value is set according to its cluster's weight ω_c. This way, the load duration curve of the centroid values has the same number of values as the load duration curve of the historical values. The amount of values per time series is denoted by $n(I)$.

$$RMSE(\bar{V}_{LDC}) = \frac{1}{n(S)} \sum_{s} \sqrt{\frac{1}{n(I)} \sum_{i} \left(v_{s,i} - \bar{v}_{s,i}\right)^2}$$

By analogy with $RMSE(\bar{V})$, $RMSE(V^*)$ denotes the average root mean square error per time series between historical values $v_{s,d,\tau}$ and the values of their corresponding representative day $v^*_{s,c,\tau}$.

$$RMSE(V^*) = \frac{1}{n(S)} \sum_{s} \sqrt{\frac{1}{n(D)n(T)} \sum_{c} \sum_{d \epsilon D_c} \sum_{\tau} \left(v_{s,d,\tau} - v^*_{s,c,\tau}\right)^2}$$

$RMSE(V^*_{LDC})$ denotes the average root mean square error per time series between the historical values' load duration curves and the respective load duration curves consisting of the representative days $v^*_{s,i}$.

$$RMSE(V^*_{LDC}) = \frac{1}{n(S)} \sum_{s} \sqrt{\frac{1}{n(I)} \sum_{i} \left(v_{s,i} - v^*_{s,i}\right)^2}$$

Table A.1 shows the values of these error metrics depending on the number of representative days.

Table A.1: Error values depending on the number of clusters (i. e. representative days)

	$RMSE(\bar{V})$	$RMSE(\bar{V}_{LDC})$	$RMSE(V^*)$	$RMSE(V^*_{LDC})$
1 cluster	0.132	0.113	0.136	0.095
2 clusters	0.113	0.079	0.126	0.057
5 clusters	0.106	0.062	0.126	0.045
10 clusters	0.101	0.054	0.121	0.031
20 clusters	0.098	0.048	0.119	0.023
50 clusters	0.092	0.041	0.115	0.014
100 clusters	0.089	0.037	0.111	0.010

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Chapter 4

The European renewable energy target for 2030 - An impact assessment of the electricity sector *

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The European renewable energy target for 2030 – An impact assessment of the electricity sector

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HIGHLIGHTS

- A renewable (RES) target of 27% is the cost-effective share for 40% GHG reduction.
- For the electricity sector the RES-E share varies between 43% and 56%.
- Long-term costs for higher RES-E shares are less than 1% of total system costs.
- There are large differences in RES deployment and costs between Member States.
- A lack of a governance mechanism makes the EU-wide RES target difficult to achieve.

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ABSTRACT

The European Union set binding targets for the reduction of greenhouse gases (GHG) and the share of renewable energy (RE) in final energy consumption by 2020. The European Council agreed to continue with this strategy through to 2030 by setting a RE target of 27% in addition to a GHG reduction target of 40%. We provide a detailed sectoral impact assessment by analyzing the implications for the electricity sector in terms of economic costs and the regional distribution of investments and shares of electricity generated from renewable energy sources (RES-E). According to the Impact Analysis by the European Commission the 27% RE target corresponds to a RES-E share of 49%. Our model-based sensitivity analysis on underlying technological and institutional assumptions shows that the cost-effective RES-E share varies between 43% and 56%. Secondly, we quantify the economic costs of these variants and those which would be incurred with higher shares. The long-term additional costs for higher RES-E shares would be less than 1% of total system costs. The third aspect relates to the regional distribution of EU-wide efforts for upscaling renewables. We point out that delivering high RES-E shares in a cost-effective manner involves considerably different efforts by the Member States.

1. Introduction

Since 2009 the European Union (EU) has adopted an explicit target for the share of renewable energy (RE) in the provision of gross final energy consumption. This was agreed upon in the context of the "EU climate and energy package" (the so-called 20-20-20 package) that includes: (i) a 20% reduction in EU greenhouse-gas (GHG) emissions from those of 1990, (ii) raising the share of RE in the EU's final energy consumption to 20% (including a renewable share of 10% in the transport sector), and (iii) a 20% improvement in the EU's energy efficiency. The RE target has been converted to provide mandatory national targets that differ across Member States, considering their different starting points in terms of energy mix, renewables potential, GDP and past efforts (European Union, 2009). In aggregate, the share of RE has been steadily increasing; its share in gross final energy consumption rose from just above 8% in 2004 to 14% in 2012 (Eurostat, 2014a).

In order to provide long-term policy targets, a continuation of the RE target was discussed within the negotiating process for a 2030 framework for climate and energy policies (Geden and Fischer, 2014). In October 2014, the European Council set targets of at least 40% for domestic GHG reduction, and at least 27% for the RE share in final energy consumption (European Council, 2014). In addition, an indicative target of at least 27% is set for the improvement of energy efficiency. While the Commission's Impact Assessment has analyzed two variants of the 40% GHG reduction scenario with different combinations of energy efficiency and

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renewable target (European Commission, 2014b), a detailed analysis of the consistency between the individual targets is missing (see Flues et al. (2014) for an analysis of the electricity sector with a stylized model). In addition, a detailed sectoral impact assessment, for example of the transport sector, the electricity sector or the agriculture sector was not part of the Commission's analysis and is so far only rarely provided in the literature (see Enerdata (2014) for an analysis of the electricity sector).

With our analysis we close this gap for the electricity sector by providing an in-depth analysis of the share of electricity generated from renewable energy sources (RES-E) under a range of technological and institutional assumptions. We also identify the implications on economic costs and the effort sharing across the Member States. The motivation to concentrate on the electricity sector is that it already plays and will play a major role for the decarbonization effort particularly in the short-term (Knopf et al. (2013a) and IPCC (2014): In recent years the European RES-E share increased significantly, reaching 23.5% in 2013 (Eurostat, 2014b). According to the Commission's Impact Analysis (European Commission, 2014b) the energy-system wide 27% RE target is consistent with a 49% RES-E share. This considerably higher sectoral share underlines the importance of the electricity sector in delivering the overall target.

For the quantitative analysis, we utilize a refined version of the European electricity sector model LIMES-EU that was first published in Haller et al. (2012a) for an analysis of the long-term decarbonization of EU's electricity system. The modeling framework LIMES (**L**ong-term **I**nvestment **M**odel for the **E**lectricity **S**ystem) was also applied in Ludig et al. (2011, In press) and Haller et al. (2012b). Nahmmacher et al. (2014a) provide an in-depth documentation of the modeling setup used in this analysis and Nahmmacher et al. (2014b) describe the refined approach for modeling the integration of variable renewable sources across Europe. Results in the Commission's Impact Assessment are derived from an analysis based on one single energy system model, namely PRIMES (Capros et al., 2014; E3MGLab, 2011), with a limited set of alternative scenarios and is thus subject to a variety of specific model- and data-related input assumptions. In this paper we provide an in-depth sensitivity analysis of the electricity sector with LIMES-EU to assess the robustness of the results and the implications on costs and distribution. This aspect is missing in the EU Commission's Impact Assessment.

The figure of 27% for the RE share is derived from the EU Commission's own modeling analysis (European Commission, 2014b). The scenario that achieves a 40% GHG reduction in 2030 results in a RE share of 26.5%. This means that, based on this analysis, a 27% share of RE is the cost-effective share when a target of 40% GHG emission reduction is set. This is an important aspect often neglected in the debate; it indicates that the renewable target of 27% does not generate any additional burden for the deployment of renewables beyond its contribution to the reduction of GHG emissions. Conceptually, it also means that in the presence of a binding CO_2 policy, for example a price on carbon, specific subsidies for renewables are only justified when other externalities such as learning spillovers exist. In this paper, we refer to this benchmark as the "cost-effective RE target", meaning the share of RE that is necessary to achieve the 40% climate target at least costs over time.[1] Given these conditions, the European Commission's modeling has shown that to achieve a reduction of 40% GHG emissions, it is cost-effective to deploy 27% renewables by 2030. In the months before the Council's decision there was a political debate regarding whether a separate RE target is actually necessary. In the policy arena, an additional RE target is often justified by referring to its potential co-benefits, such as employment effects, local added value, additional environmental benefits and industrial policy (Edenhofer et al., 2013a, 2013b; Lehmann and Gawel, 2013; Bruckner et al., 2014), although the evidence of these co-benefits is highly disputed (Borenstein, 2012). Renewable energy policy has a long tradition in Europe: back in 1986 the promotion of renewables was one of the Community's energy objectives (Kanellakis et al., 2013). The European Commission explicitly states that "increased shares in renewables […] contribute to more indigenous energy sources, reduced energy import dependence and jobs and growth" (European Commission, 2013b). The EU Council conclusions define an "at least" 27% RE target, implying that a higher target might be possible if individual Member States set their own national targets at a higher level. If this is the case, and the RE share is meant to be higher than that which is cost-effective, we postulate that the underlying rationale is based on considerations other than climate change mitigation. However, in the official analysis there is no quantification of the costs of a RE target which is additional to that for GHG reduction.

For the electricity sector, our modeling framework can provide an analysis of the cost-effective RES-E share given an exogenously specified long-term decarbonization pathway. Within our optimization framework, a RES-E share that is forced to be higher than the cost-effective share always leads to additional costs. These costs can, in principle, be weighed against the expected co-benefits. In this paper we compute the additional costs for a higher than cost-effective RES-E share, being one side of the equation of the political debate. The quantification of potential co-benefits is beyond the scope of the paper.

A further aspect we highlight is that, although the effort to achieve the GHG target is incorporated into nationally binding targets at individual Member State level for the sectors not covered by the European Emissions Trading Scheme (ETS), the RE target needs to be "delivered collectively" (European Council, 2014). In their Energy Union Package of March 2015 the EU Commission states that they will "propose a new Renewable Energy Package in 2016–2017 including […] legislation to ensure that the 2030 EU target is met cost-effectively" (European Commission, 2015). An EU-level target might be difficult to achieve as although some form of governance mechanism is anticipated (European Commission, 2014a), Europe is rather politically divided over the importance of a renewable target at all (Evans, 2014) and yet there is no explicit effort sharing rule designed to achieve the RE target at the EU level. We analyze the cost-effective distribution of the RES-E share across the Member States and draw some conclusions concerning the infrastructure requirements, import/export balances and European effort sharing on renewable deployment.

In summary, this paper provides an impact assessment of the electricity sector and draws conclusions on the following key research questions in order to inform the political debate:

1. What is the cost-effective RES-E share in the year 2030 that is consistent with a long-term decarbonization pathway until 2050, given variants of key technology and institutional input assumptions? Which RES-E technologies make important contributions?
2. What are the economic costs of these variants and those of a RES-E share enforced to be higher than the cost-effective one?
3. What does the setting of the RE target at the European level (rather than at Member State level, as for 2020) imply for its distribution across countries? What would cost-effective effort sharing look like? Which countries are likely to contribute most to the overall RES-E provision?

[1] It also refers to the economic welfare perspective on these costs in contrast to costs seen by individual market participants. Our specific analysis only examines the electricity sector, rather than the overall economy.

Table 1
Overview of scenarios.

	Technology/Institution	Issue	Scenario name
	Default scenario as in "GHG40" of the Impact Assessment by the EU Commission (2014b) and as agreed by the European Council (2014)		Default
Technology setting	Nuclear Power	Phase-out until 2030	NucOut 2030
		Phase-out until 2050 (−50% in 2030)	NucOut 2050
	CCS	Not available	NoCCS
	vRES-E (wind, solar)	Higher investment costs (+10% in 2020; +20% in 2030 and thereafter)	High cost vRES-E
		Lower investment costs (−10% in 2020; −20% in 2030 and thereafter)	Low cost vRES-E
		Only sites with average capacity factors	Low pot vRES-E
	Storage	Higher investment costs (+100%)	High cost stor
	Biomass	Higher fuel costs (+100%)	High cost bio
Institutional setting	Transmission capacity expansion process	No capacity expansion beyond today, completion of internal market impeded	No trans exp
		Faster capacity expansion/market integration (expansion rate +100%)	High trans exp
	Energy security concerns	More than 95% of electricity supply from domestic power plants	95% national
	Success of energy efficiency programs	Electricity demand lower by 5% in 2030 and thereafter	Demand −5%
		Electricity demand lower by 10% in 2030 and thereafter	Demand −10%
Policy ambition	Minimum 55% RES-E share in 2030 and thereafter		RES-E 55%
	Minimum 60% RES-E share in 2030 and thereafter		RES-E 60%
	Minimum 65% RES-E share in 2030 and thereafter		RES-E 65%
	Reference scenario of the European Commission (2013a) with only 44% GHG reduction by 2050 (instead of 80%)		low GHG target

The remainder of this paper is structured as follows. The method of the analysis is illustrated in Section 2, introducing the model LIMES-EU (Section 2.1) and the scenario setup (Section 2.2). We present and discuss the modeling results in terms of sensitivity analysis, costs and regional distribution in Section 3. Section 4 concludes and derives policy implications.

2. Method

2.1. The electricity system model LIMES-EU

The European electricity system model LIMES-EU (Nahmmacher et al., 2014a, 2014b, Haller et al., 2012a) is designed to generate quantitative scenarios that represent a consistent, system-cost optimal transition towards a decarbonized European electricity system in 2050. In its current version the partial equilibrium model comprises 26 of the 28 EU Member States[2] plus Norway, Switzerland and the Balkan region. The capacities of generation and storage technologies are aggregated nationally, with each country constituting one model region.[3] The transmission grid in LIMES-EU is represented by Net Transfer Capacities (NTCs) between the model regions. Electricity exchange with regions outside the modelled area is not possible. The model is calibrated to the base year 2010, for which installed power generation and storage capacities are fixed according to Platts (2011) and Eurostat (2013b). The installed transmission network is reflected by the NTC summer values of 2010 as reported by ENTSO-E (2013).

Endowed with perfect foresight, LIMES-EU yields a social planner solution that optimizes the following features in time steps of 5 years for each model region: (i) dispatch and curtailment of installed electricity generation technologies, (ii) electricity import balance between neighboring model regions, (iii) investments into installed capacities of electricity generation technologies and (iv) investments into NTCs between model regions. Specified as a linear optimization model, the objective function of LIMES-EU is to minimize the total discounted[4] electricity system costs (comprised of fuel, investment, fixed and variable operation and maintenance costs) of all model regions between 2010 and 2050. It assumes an exogenous demand for electricity and a number of technological and political boundary conditions, for example nuclear phase-out in certain Member States. Climate policy is simulated by constraining annual CO_2 emissions (see following section for individual scenario setups).

A new time-slice approach was developed to account for fluctuating feed-in of variable renewable electricity (vRES-E) and differences in electricity demand occurring on time scales that require higher than annual resolution Nahmmacher et al., (2014b). It is designed to reflect: (i) the annual electricity demand and average vRES-E capacity factors for each region, (ii) the region-specific load duration curves of electricity demand and vRES-E technologies, and (iii) the spatial correlation of electricity demand and vRES-E supply across regions. Nahmmacher et al. (2014b) present the details of this procedure and show that a total of 48 time slices are appropriate to model the crucial features of vRES-E generation in Europe with LIMES-EU. It appears that spring and fall days can be represented in similar time slices and fewer time slices are required for summer days than winter days because there is less variation. With this computationally efficient method we are able to give an appropriate representation of vRES-E within Europe, which is crucial when analyzing potential RES-E shares for the year 2030.

In this modeling framework it is clear that an exogenously enforced RES-E share that is higher than the cost-effective RES-E share will always lead to additional costs. This is because LIMES-EU is an intertemporal optimization model endowed with perfect foresight that takes into account only the climate externality – in such a framework additional biding constraints always lead to additional costs. The aim of the analysis in Section 3.2 is to quantify these costs. It should also be clearly stated here that, in this model setting, we can neither explore potential co-benefits nor address other externalities resulting from RES-E deployment.

[2] The island states of Malta and Cyprus are not included in the current model version.

[3] With the exception of the non-EU countries in the Balkan region that are grouped to one model region.

[4] We apply a social discount rate of 5%.

This includes learning and spillover externalities or externalities at the diffusion site.

2.2. Scenario setup

We deploy a large number of scenarios to assess the robustness of the 49% RES-E share in 2030 with respect to technological, institutional and policy parameters and settings. Except for the "low GHG target"[5] scenario, all scenarios are required to meet the same CO_2 reduction pathway until 2050. The pathway is designed according to the "Roadmap for moving to a competitive low carbon economy in 2050" (European Commission, 2011), which suggests a strong decarbonization of the electricity system by 2050 with an emission reduction of about −95% compared to 1990. The intermediate annual emission limits are decreasing linearly between 2010 and 2050, resulting in a 52% reduction by 2030 compared to 1990. For all scenarios these emission reduction requirements in the electricity sector are applied as boundary conditions. In order to be comparable with the Impact Assessment (European Commission, 2014b), we configure our "default scenario" with techno-economic and policy assumptions similar to its scenario "GHG40". We also provide an in-depth sensitivity analysis of the electricity sector that is not part of the EU Commission's Impact Assessment. The parameters we vary include nuclear and carbon capture and sequestration (CCS) policy, biomass availability, wind and solar cost development, transmission capacity, electricity demand, electricity storage capacity, and transmission capacity. In addition, we evaluate scenarios with a higher than cost-effective RES-E share and one scenario with a lower level of emission reduction. See Table 1 for an overview.

The following paragraphs substantiate the chosen variants and describe how they drive the model.

Nuclear power is a heavily disputed source of electricity in Europe. As a default assumption, we implement a nuclear phase-out in Germany, Belgium and Switzerland. New installations in other countries are limited to those currently under construction or planned,[6] or those required to replace depreciated capacities. Whether nuclear power will be part of the European electricity mix of the future is ultimately a political decision. In order to evaluate the implications of a nuclear-phase out across Europe we consider two scenarios. One assumes a complete nuclear phase-out in each modelled country by 2030 (NucOut 2030). The other scenario assumes a reduction of 50% of today's national nuclear capacities by 2030 and a phase-out by 2050 (NucOut 2050).

The question of whether it will be legally possible to deploy CCS facilities in Europe is likewise a political choice. Whether it will be economically viable is ultimately a question of technology cost developments. In the default scenario we allow CCS for the combustion of lignite, hard coal and natural gas; consult Table A2 in the Appendix for the techno-economic parameters. The scenario NoCCS assumes that political and technological hurdles related to the deployment of CCS across Europe cannot be overcome (compare von Hirschhausen et al. (2012)).

It is highly uncertain how investments cost and storage solutions for the vRES-E technologies (onshore and offshore wind, solar photovoltaic (PV) and concentrated solar power (CSP)) will develop over the coming decades. In the default scenario we use the same vRES-E investment costs as in the Impact Assessment (European Commission, 2014b) (see Table A1 in the Appendix). The high (low) cost vRES-E scenario assumes that investment costs of vRES-E technologies will develop less (more) favorably. A separate scenario (high cost stor) evaluates the impact of storage solutions being more capital-intensive than assumed in the default setting (see Table A2 in the Appendix).

A further parameter that is uncertain but crucial is a country's wind and solar power technical potential. In LIMES-EU it is a function of the installable capacity of wind and solar power plants, which depends on each country's size and land structure as well as the achievable capacity factor at each site. Details of our assumptions for deriving the vRES-E potential are provided in Nahmmacher et al. (2014a, 2014b). In order to reflect the circumstance in which the useable wind and solar power potential is lower than anticipated, for example due to lower social acceptance of wind power plants or other empirically observed factors (Boccard, 2009), we calculate one scenario using solely average capacity factors (low pot vRES-E).

The biomass potential incorporated in LIMES-EU is based on data from EEA (2006) which gives the environmentally-compatible bioenergy potential from agriculture, forestry and waste. We assume that one-third of the potential stated in EEA (2006) is eligible for electricity production in LIMES-EU as not all of the total biomass potential can be deployed at competitive prices and the transport and heat sector also utilize a considerable amount of the available biomass stock. Where the potential calculated for a specific country[7] is smaller than its biomass deployment target stated in the National Renewable Energy Action Plans (NREAPs) (European Commission, 2013c), the potential is increased to meet the target.[8] The default scenario's biomass and fossil fuel prices are stated in Table A3 in the Appendix. In order to evaluate the impact of higher fuel prices for biomass we consider one scenario in which they are doubled (high cost bio).

In addition to the technology variants, we analyze scenarios that represent different institutional settings. An important factor is the speed and degree to which transmission capacities can be expanded beyond today's performance level (Schmid and Knopf, 2014). The default annual expansion of cross-border transmission capacities is restricted to 0.2 GW of net-transfer capacity (NTC) per cross-country connection. This constraint serves as a proxy for the limit on the achievable speed of capacity expansion, which may be imposed, for example, by social or bureaucratic considerations. We consider two extreme variants to represent a slower, more nationally focused situation and a faster, decisive integration of the European electricity market; one scenario does not allow for any transmission capacity expansion beyond today's level (no trans exp), while the other allows a doubling in the upper limit of capacity expansion to 0.4 GW per year of net-transfer capacity (NTC) per cross-country connection.

Further institutional issues are energy security concerns and energy efficiency. Regarding the first we implement a scenario in which each country has to supply 95% of electricity from domestic power plants (95% national), i.e. net imports of each model region must not exceed 5% of domestic electricity consumption. To provide a proxy for successful energy efficiency programs we reduce the annual electricity demand of the default case by 5% (10%) in 2030 and thereafter, in the demand-5% (demand-10%) scenario. The default assumptions for future electricity demand are reported in Nahmmacher et al. (2014a). Final electricity demand in the model's calibration year 2010 is retrieved from Eurostat (2013a)

[5] The "low GHG target" scenario is based on the reference scenario of the European Commission (2013a, 2013b, 2013c, 2013d) with only 44% overall GHG reduction by 2050, with power sector CO_2 reductions at about 73% by 2050.

[6] According to the World Nuclear Association (2013) new nuclear capacities under construction or planned are: Belgium (1.9 GW), Czech Republic (2.4 GW), Finland (1.7 GW), France (3.44 GW), Great Britain (3.8 GW), Lithuania (1.35 GW), Poland (6 GW), Romania (1.31 GW) and Slovakia (0.88 GW).

[7] Biomass potentials of countries for which no data is available in EEA (2006) are calculated based on the extent of arable land and forests (FAO, 2013) as well as the land structure and biomass potential of the surrounding countries with available data.

[8] This is the case for Belgium, Denmark, Luxemburg and the Netherlands.

and IEA (2012). Demand projections up to 2050 are taken from the projections of the European Commission (2014b). For regions not included, demand growth rates are estimated based on the growth rates of their neighboring countries for which data is available.

Finally, we consider the pursuit of a less ambitious mitigation policy ("low GHG target") – as reflected in the European Commission's reference scenario. This assumes GHG emission reductions of 32% by 2030 and 44% by 2050 (European Commission, 2013a). This is the equivalent of a 41% CO_2 emission reduction in the electricity sector by 2030 and 73% reduction by 2050.

In order to investigate variants of the default scenario in which a higher then cost-effective RES-E share is set for 2030 we consider scenarios that have an imposed share of 55%, 60%, and 65% in that year (see the bottom of Table 1). In these model runs, a constraint enforces the RES-E share to remain at least at this level from the year 2030 onwards.

3. Results and discussion

3.1. Sensitivity analysis of the cost-effective RES-E share

This section determines the cost-effective RES-E share and technology mix for the European electricity sector in 2030 according to the LIMES-EU model. Figure 1 shows the results of the extensive sensitivity analysis for the respective technology mix of RES-E in the year 2030 (for overall electricity generation see Figure A1). We identify three main findings.

First, with LIMES-EU we find that the default scenario results in a RES-share of 50% in 2030. This is very close to the cost-effective RES-E share of 49% identified by the European Commission (2014b) in the scenario "GHG40". This implies that our analysis can be seen as a proxy for the sensitivity analysis which is missing from the PRIMES model used in the Impact Assessment.

Second, our sensitivity analysis suggests that the cost-effective RES-E share ranges from 43% to 56%, which seems quite narrow given that some of the assumptions are rather extreme. The 49% from the Impact Assessment lies right in the middle of this range. As expected, the cost-effective share is higher when nuclear or CCS are constrained or investment costs of vRES-E technologies are reduced. In contrast, the cost-effective share is lower when the investment costs of vRES-E technologies are higher, their technical potential is restricted, biomass costs are higher or electricity demand is lower than in the default case. Notably, high storage costs and all institutional assumptions have virtually no influence on the cost-effective RES-E share in 2030. Even in the scenario "low GHG target", with only 41% rather than 52% CO_2 emission reduction against 1990, the cost-effective RES-E share of 45% is within the range spanned by the sensitivities. This implies that the optimal RES-E share depends more on other uncertain input assumptions and political factors than on the overall level of emission reduction.

The third finding concerns the technology-specific uncertainty. The technology mix that emerges for 2030 is similar across all scenarios, especially for hydro and biomass. The exception is the scenario which has high costs for biomass: this has a much smaller share of bioenergy (high cost bio). In contrast, the share of vRES-E (wind and solar PV) varies considerably: between 16% and 31% (22% in the default case). This suggests there are likely to be challenges in terms of system integration, but according to IEA (2014) they seem manageable with current levels of system flexibility. Onshore wind plays a very important role in all scenarios, although its share is reduced if high quality wind sites are unavailable (low pot vRES-E) or investment costs are higher than expected (high cost vRES-E). In the scenarios in which the share of biomass is low, the difference is satisfied with a higher share of wind. Solar PV is only used to a limited extent in all of the scenarios. However, in the scenarios with the highest total RES-E share (NucOut 2030, low cost vRES, NucOut 2050), the share of solar PV is also at its highest. Concentrated solar power (CSP) does not play an important role in any of the scenarios; this technology has comparatively high costs of production in the year 2030 and is hence not deployed. CSP is only deployed in the scenario with optimistic investment cost developments (low cost vRES-E). Offshore wind is the only RES-E technology that plays an even less important role than CSP. This is primarily due to its comparatively high costs of electricity generation, relative to those of the more mature technologies onshore wind and solar PV. Future investment costs are projected to remain constant or maybe even increase (Heptonstall et al., 2012); activities for bringing down investment and particularly O&M costs are underway but show slow progress (Kaldellis and Kapsali, 2013).

In the scenarios with a higher than cost-effective share of RES-E, the additional investments into RES-E capacities between 2025 and 2030 primarily consist of solar PV and onshore wind. Also, CSP increasingly comes into play. Offshore wind is again not deployed in these scenarios, due to the prohibitively high investment costs assumed in the "GHG40" scenario of the Impact Assessment by the European Commission (2014b), which we proxy with our default scenario. The level of hydro and biomass is unaffected by the prescribed RES-E share in 2030. Upon a closer look on the development over time, they follow the same path until 2025. Between

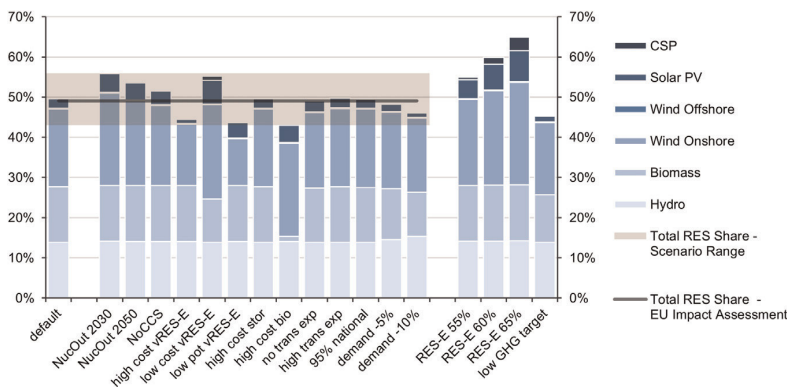

Fig. 1. Share of renewables in the European electricity sector in percent of total electricity provision and the respective technology mix of renewables in the year 2030. Gray shading indicates the range across scenarios. Source: Model results of LIMES-EU. Black line: Share of RES-E in the electricity sector in the scenario "GHG40" of the Impact Assessment for the 2030 framework by the European Commission (2014a), 49%.

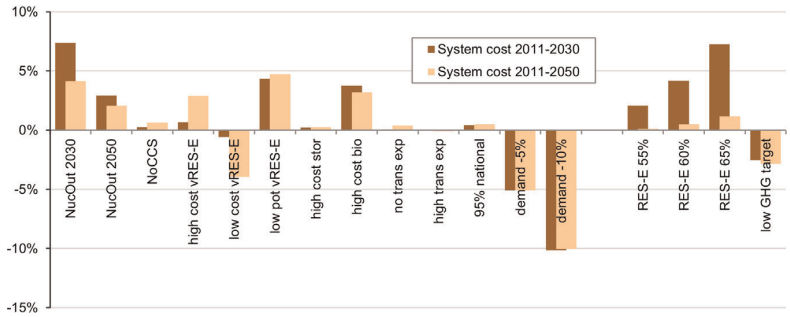

Fig. 2. Percentage difference in total discounted system costs for the different scenarios relative to the default scenario for two different time spans (2011–2030 and 2011–2050). Source: Model results of LIMES-EU.

2025 and 2030 investments in RES-E capacities are pursued as necessary to fulfill the target in 2030. Thereafter, the RES-E share stagnates over time, in all scenarios, until it meets the cost-effective trajectory for achieving the 95% mitigation target in 2050.

3.2. Economic costs

The objective function of LIMES-EU is to minimize the present value of cumulative discounted total system costs over the period 2011–2050. Hence, this is the primary indicator for analyzing the economic costs of the different scenarios.[9] Fig. 2 illustrates the differences in the present value of cumulative costs between the variants and the default scenario, for the two periods 2011–2030 and 2011–2050. It is important to take the intertemporal aspect into account, as renewables require high upfront investments but generate long-term savings in fuel costs.

Several observations are noteworthy. First, the cost differences across the variants are much higher than the difference between the default scenario and the scenario with less ambitious emission reductions (low GHG target). Second, the two most potent factors for decreasing total discounted system costs are: (i) lowering the investment costs for variable renewables and (ii) reducing electricity demand. Third, the magnitude of the differences in the economic costs of setting the RES-E share above the cost-effective share of 50% is comparable with the uncertainties resulting from different input assumptions. It is obvious that the costs increase with the level of ambition of the target. The additional costs for the higher RES-E shares however, are only noticeable in the period up to 2030. In the long-run, i.e. up to 2050, the additional costs are up to 0.9% (30 bn€) higher than that of the default scenario for a RES-E share of 65% in 2030. This is different to the NucOut 2030, low pot vRES-E and high cost bio scenarios, where the costs are high in both the medium-term to 2030 and long-term to 2050; they are nearly 4% higher than in the default setting.

The reason that the additional costs for a RES-E share higher than the cost-effective one are small for the period 2011–2050 (compared to those for the period 2011–2030) is that in the long-term a system with a high share of renewables saves fuel costs as shown in Fig. 3. In LIMES-EU, total system costs consist of investment costs, operation and maintenance (O&M) costs and fuel costs. Fig. 3 shows the relationship between each of these individual components for the scenarios with higher RES-E shares and the default scenario, for the periods 2011–2030 and 2011–2050. It shows that the largest proportion of costs are investment costs. These are nearly 50% higher in the "RES-E share 65%" scenario for the period 2011–2030 than the default scenario which does not have an additional RES-E constraint. However, in the long-term, up to 2050, these additional investment costs amount to just 10% above those in the default scenario. This is because in order to meet the higher RES-E share in 2030, substantial investment is required between 2025 and 2030, which tails off afterwards. It is important to acknowledge that investment costs are different to fuel costs, as they have the ability to stimulate economic development (Creutzig et al., 2014), for example through a multiplier effect. In contrast, fuel costs can constitute a cash outflow from the economy, if purchased from abroad. This is largely the case for fossil fuels in Europe. Also, investment costs are certain once they are incurred while future fuel prices are subject to significant volatility.

Relatively high shares of RES-E lead to a substitution of electricity generation based on fuel-cost-intensive technologies and hence to a reduction in fuel costs. In the case of LIMES-EU, this particularly leads to a lower share of gas powered plants. Hence, the fast deployment of RES-E capacities by 2030 leads to fuel cost savings, and therefore lower total system costs, in the years between 2030 and 2050. The effect of the higher than cost-effective RES-E shares on operation and maintenance costs is comparatively moderate. Overall, the relative cost increase stemming from substantially higher investment costs for RES-E capacities up to 2030 and moderately low increases in operation and maintenance costs is counterbalanced by subsequent low fuel costs. Such costs are expected to reduce by roughly 14% for the period 2011–2050. Hence, the longer the time-perspective, the lower the additional costs for a higher than cost-effective RES-E share.

Another way of looking at the costs for higher RES-E shares is to calculate the shadow price of the RES-E constraint. This shadow price indicates how much the total system costs would increase with each additionally enforced MWh of RES-E generation. This increase is linear and to reach 65% renewables by 2030, a shadow price of almost 75 €/MWh for RES-E-based electricity is reached. Note that in the 60% and 65% scenarios, the respective RES-E constraint leads to such a high deployment of RES-E capacities that the CO_2 emission pathway becomes a non-binding constraint. Hence, the shadow price of CO_2 emissions decreases to zero in this case.

In principle, these economic costs could be balanced against potential co-benefits, for example employment effects or health benefits, of additional RES-E deployment. According to the IPCC (2014), co-benefits refer to "positive effects that a policy or measure aimed at one objective might have on other objectives, without yet evaluating the net effect on overall social welfare". However, this calculation is not straightforward and there are only few attempts found in literature (McCollum et al., 2013). Most approaches have considerable methodological shortcomings and it is important to realize that co-benefits are ignored in the model used in the European Commission's quantitative analysis; only the climate mitigation target is considered endogenously. The main

[9] If not mentioned otherwise, all prices and costs stated in this paper are measured in $€_{2010}$

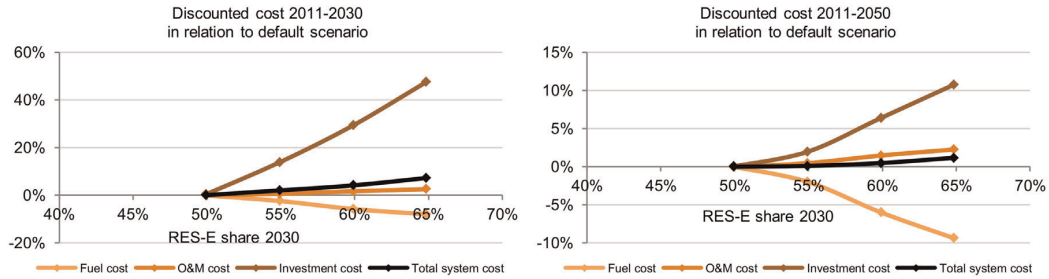

Fig. 3. Discounted costs over the period 2011–2030 (left) and 2011–2050 (right) for scenarios with different exogenously enforced RES-E shares from 2030 onwards, shown in percentage terms relative to the default case with an endogenous RES-E share in 2030. Given are the different cost components of the total system costs: fuel costs, operation and maintenance (O&M) costs and investments costs. All scenarios have the same emission reduction target. Source: Model results of LIMES-EU.

reason for this is because most existing energy system models are incapable of representing the underlying processes of co-benefits of RES-E in sufficient detail. Instead, in the Impact Assessment (European Commission, 2014b) an accounting of co-benefits is derived ex-post using other models that also face some conceptual shortcomings (Knopf, 2014).

3.3. Analysis of the regional distribution

The 2030 target for renewables is formulated in order to deliver the overall RES-E deployment at EU level. However, the contribution required by each Member State remains unresolved. A number of analyses have indicated that the regional distribution is especially important, taking into account the aspect of a *fair* effort sharing within the EU (Boratyńsk et al., 2014; Enerdata, 2014). For GHG emission reduction in the sectors not covered by the European Emissions Trading System (EU-ETS), the individual countries' reduction efforts will be distributed on the basis of relative GDP per capita (European Council, 2014). For the renewables in the electricity sector the NREAPs apply until 2020 and specify national RES-E targets based on RES-E shares in 2005, renewables potential, GDP and past efforts (European Union, 2009). For the 2030 target however, the regional distribution of the RES-E share remains unresolved, except that different levels of ambition are clearly expected for different Member States. Our results show the cost-effective effort sharing required between Member States to achieve the overall target.

Fig. 4 (left) shows the individual countries' RES-E share in 2030. As the resource potential is quite different across the countries, it is not surprising that individual Member States contribute quite differently towards the overall target. For example, Norway has a high RES-E share due to hydro, while in France, where nuclear plays a large role, the share is smaller. It also shows that the diversity in electricity mix across Member States is substantial and even increases towards 2030 (see also Knopf et al. (2013b)).

The right panel indicates that this scenario comes with a significant expansion of net transfer capacities across Europe which are particularly strengthened in central-Western Europe (between France, Germany, Belgium, Luxemburg). The connections to southern Europe and between Great Britain and Ireland as well as between the Baltic and Nordic states are also reinforced. The countries indicated in orange (blue) will turn into net importers (exporters). The Baltic States and Denmark will export renewable electricity generated by newly installed wind turbines. These results indicate that it is highly reasonable to combine the formulation of the RE target in 2030 with an explicit infrastructure package.

Given that the status-quo of the RES-E share differs considerably among the different Member States with some having a high share already today, it makes sense to examine the percentage increase required to upscale renewables in the timeframe between 2010 and 2030 (Fig. 5, left). It is important to note that the effort is quite diverse across Europe with some countries upscaling by nearly 80 percentage points between 2010 and 2030, while other countries only show an increase of 10 percentage points. For those countries that already provide a high share of renewables, for example Norway or Sweden, little upscaling effort is required (or possible), but countries with a much smaller RES-E

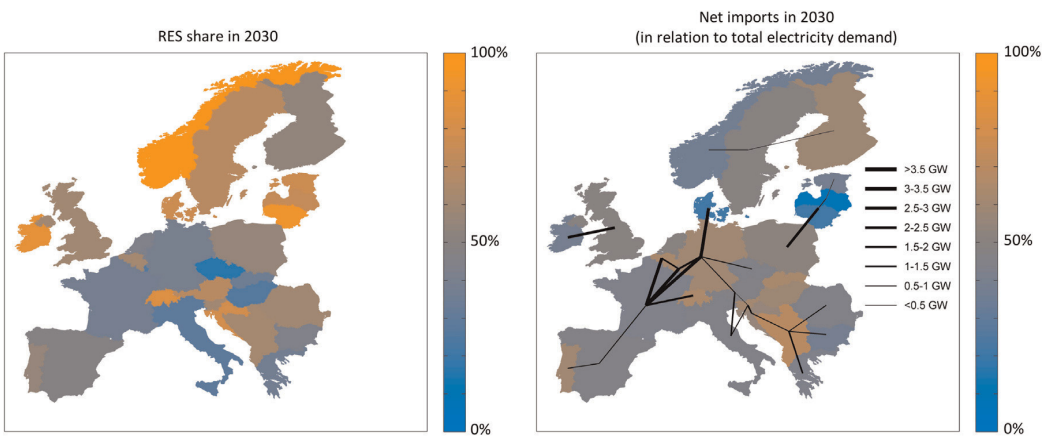

Fig. 4. Share of RES-E in electricity generation for the year 2030 (left) and additional transmission capacities installed between 2011 and 2030 and the export/import balance (right) for the default scenario. Source: Model results of LIMES-EU. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

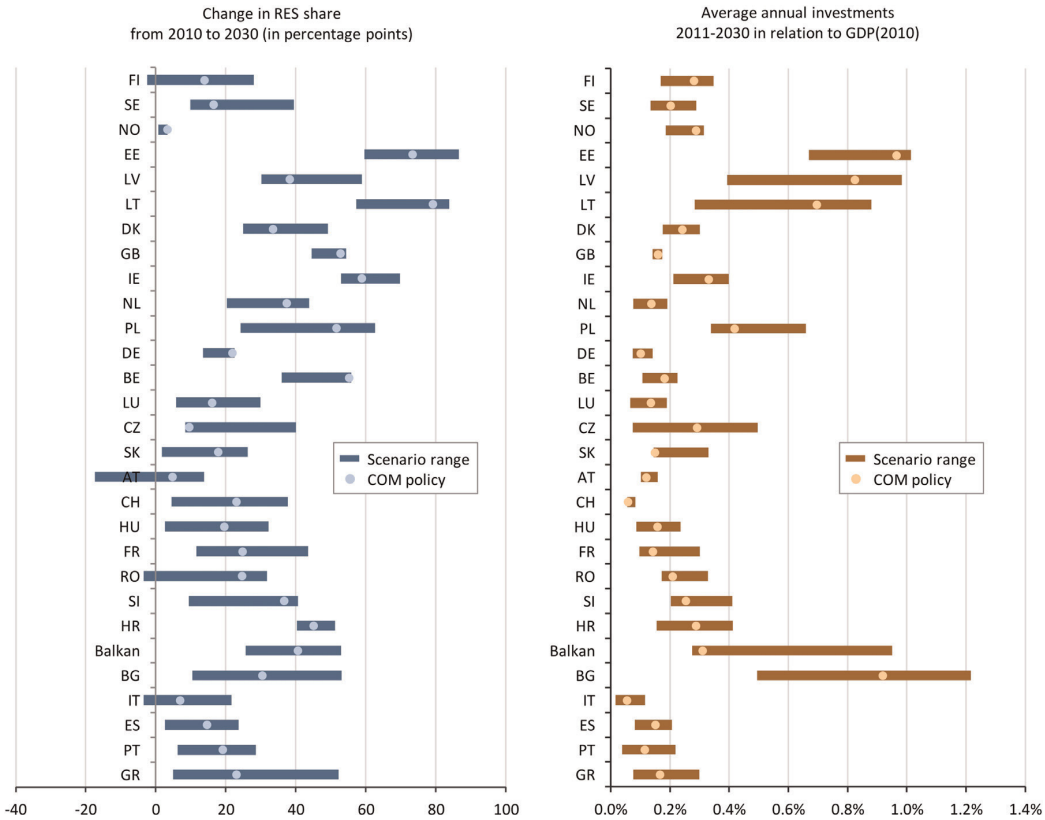

Fig. 5. Percentage change in RES-E shares as a proportion of electricity production (left) and average annual investments in RES-E capacities over the period 2011–2030 compared to each country's GDP in 2010 (right). The range displayed is as implied by the technology and institutional variants, the default scenario and the RES-E share scenarios. The scenario range refers to Table 1. Member States are ordered from north (top) to south (bottom). Source: Model results of LIMES-EU.

Table A1
Investment costs for vRES-E technologies in €/kW. Source: European Commission. (2014b)

	Solar		Wind	
	PV	CSP	Onshore	Offshore
2010	2500	5500	1300	4750
2015	2004	4329	1296	4412
2020	1508	3158	1291	4073
2025	1297	2859	1262	3790
2030	1085	2560	1232	3507
2035	1011	2411	1212	3338
2040	937	2262	1191	3168
2045	862	2112	1171	2999
2050	788	1963	1150	2829

share (e.g. Poland, the Baltic countries or Great Britain) have to make considerable investments in RES-E in order to achieve the overall GHG reduction target. In general it seems that the countries in the north (upper part of the figure) have to contribute more than southern countries to the overall provision of renewable deployment. This is strongly related to the finding in Fig. 1 that wind is the most important future renewable electricity source in LIMES-EU.

While the left panel of Fig. 5 provides an impression of the technical transformation required for each Member State, the right panel illustrates the RES-E capacity investment needed as a proportion of each country's GDP in 2010. This indicates the economic transformation requirement. For most countries, the investment requirement is much lower than 0.5% of their GDP regardless of scenario. There are, however, some exceptions: the Baltic States (Estonia, Latvia, Lithuania), Poland, the Balkan region and Bulgaria indicate investment requirements ranging from 0.5% to 1% of their GDP. This diversity across Member States is a problem that has to be addressed by an appropriate governance structure and effort sharing mechanism. Such a governance mechanism needs to take into account: (i) the different starting positions, (ii) the different RES-E potentials, and (iii) the different investment cost requirements as a proportion of GDP.

It should be noted that this analysis only gives the cost-effective benchmark for the distribution of effort. Europe is, however, rather divided over the importance of renewables and some of those countries that could in principle – according to the model results – provide a high share of renewables, for example Poland, are opposed to binding and ambitious renewable targets. In that sense, a fair effort sharing could help to bring the transformation more in line with the cost-effective benchmark.

4. Conclusions and policy implications

In October 2014 the European Council agreed on the headline targets for 2030 with domestic GHG reductions of at least 40%, a binding EU wide target of at least 27% renewables and an indicative target of 27% energy efficiency. Based on an extensive modeling analysis of the European electricity sector, we address three major questions that arise in the context of setting a renewable target for 2030 debated in the political arena: (i) what is the cost-effective RES-E share for the year 2030 that is consistent

Table A2
Techno-economic characteristics of thermal technologies and storage solutions. Source: Schröder et al. (2013), European Commission (2014b), Haller et al. (2012a, 2012b), Schmid et al. (2012) and own assumptions.

Technology	Investment cost (€/kW)	Efficiency new (old) (%)	Annual availability (%)	Fixed O&M cost (% of inv. cost)	Variable O&M cost (€/MWh)	Lifetime (years)
Nuclear	4000	33	80	3	2.8	60
Hard coal	1500	44 (37.4)	80	2	6.85	50
Hard Coal CCS	2600	38	80	2	11.42	50
Lignite	1800	43 (36.6)	80	2	9.13	50
Lignite CCS	3000	37	80	2	14.6	50
Gas CC	800	60	80	6	0.525	40
Gas CC CCS	1600	52	80	6	5.525	40
Gas GT	400	35	80	4	0.525	40
Hydro	2500	100	Region specific	2	0	80
Biomass	2000	42	80	4	2.89	40
Intraday storage	1500	80	100	0.5	0	80
Interday storage	2500	70	100	1	0	20

Table A3
Fuel costs in €/GJ. Source: European Commission (2014b) and own assumptions.

Year	Hard coal	Lignite	Natural gas	Uranium	Biomass
2010	1.8	1.0	5.4	0.5	2.5
2015	2.2	1.0	6.2	0.6	2.5
2020	2.6	1.0	6.9	0.7	2.5
2025	2.6	1.0	7.1	0.8	2.5
2030	2.7	1.0	7.3	1.0	2.5
2035	2.9	1.0	7.2	1.2	2.5
2040	3.1	1.0	7.2	1.4	2.5
2045	3.3	1.0	7.1	1.7	2.5
2050	3.5	1.0	7.0	2.0	2.5

with a long-term decarbonization pathway until 2050? (ii) what are the economic costs of setting RES-E shares higher than the cost-effective one? (iii) what does the formulation of the RE target at the European level (rather than Member State level, as for 2020) imply for the distributional question?

In brief, the answers to these questions are: (i) the RE target of 27% is the cost-effective share in line with 40% GHG reduction; this RE target corresponds to a RES-E share of 49% in the electricity sector. Our model-based sensitivity analysis shows that the cost-effective RES-E share for the long-term decarbonization of the electricity sector varies between 43% and 56%, (ii) the costs for a higher than cost-effective target are less than 1% of total discounted system costs over the period 2011–2050, but (iii) the distributional question and the missing governance mechanism for the EU-wide target might render the achievement of the target very difficult.

Based on our analysis we can conclude that an exogenously enforced RES-E share that is only slightly above the cost-effective one will not incur large additional costs. However, a target with a strong emphasis on RES-E deployment has notable implications on the overall system costs. This is particularly the case for the period 2025–2030, when substantial funding needs to be provided for deploying the required RES-E generation capacities. This analysis cannot answer the question of whether or not it is reasonable to set an additional renewables target. However, our results emphasize that there are large uncertainties in future price developments, institutional settings and the availability of technologies such as nuclear or CCS. These uncertainties have been taken into account in our sensitivity analysis. It turns out that these uncertainties increase the costs in a similar order of magnitude as a RES-E share that is higher than the cost-effective one.

Our analysis has important policy implications on infrastructure planning and on a governance mechanism for achieving the EU-wide RE target:

- While the focus is often only on the deployment of renewables, the required pan-European transmission grid expansion is also affected by the RE target. Cross-border effects are particularly noticeable in the renewables electricity sector; for example some countries will become considerable exporters or importers of electricity. In this respect, renewable deployment cannot be disentangled from infrastructure planning. The current version of the Ten-Year Network Development Plan details network reinforcements based on two RES-E capacity visions in 2030, which essentially represent an aggregate of country-specific bottom-up plans (ENTSO-E, 2014a). However, future versions should also consider a more common and cost-effective solution across Europe (ENTSO-E, 2014b). A more dedicated and transparent analysis of the distributional question in

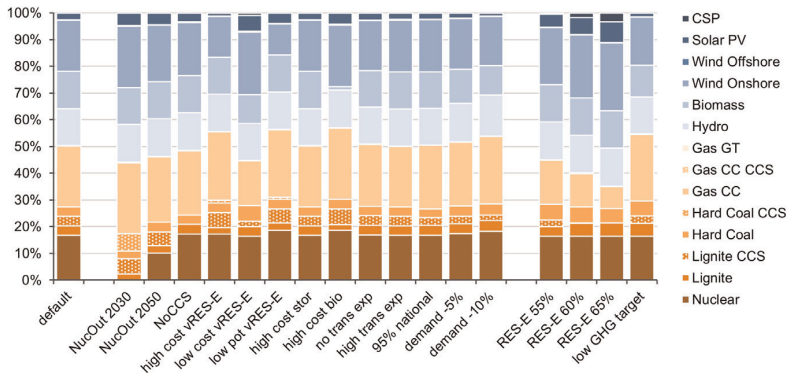

Fig. A1. Electricity generation in the year 2030 for the different scenarios under investigation. Source: Model results of LIMES-EU.

the context of pan-European network planning is highly recommendable. At best, these processes should be intertwined with the regionalization of the 2030 RE target; the EU-wide target could, for example, be broken down into targets for specific regions. In addition, it would seem reasonable to develop a dedicated infrastructure package that accompanies the RE target.

- A new aspect in the EU framework for 2030 is that the RE target is only defined at EU level, in contrast to the framework for 2020 where national renewable deployment plans had to be provided by each Member State (EEA, 2012). Our analysis shows that the upscaling effort required to produce renewables is quite different across the Member States. In order to accommodate these differences, one idea could be to install a financial effort sharing mechanism. As no Member State has an individual obligation to provide renewables however, it is unlikely that countries would be willing to pay for the upscaling of RES-E deployment in other Member States. An effort sharing framework for achieving the RE target would also have to consider the co-benefits that are associated with the deployment of renewables. Such a framework might be different from that required for emission reduction. In the latter case a global public good is produced (decreased risk of impacts from climate change), while the production of renewables also generates a local public good through the provision of co-benefits.

To conclude, although model results provide a clear indication that the overall RE target seems to be achievable, in political reality it is unclear which kind of governance mechanism will be able to deliver the target of 27%. The model assumes an exogenous enforcement of policies, but it is not clear whether this will be seen in reality. Some argue that an important aspect of a RE target is to foster coordination (Klinge Jacobsen et al., 2014). Given the observation that achieving the 20% renewables target by 2020 will be difficult however (European Commission, 2013d), there is a clear danger that the 27% target for 2030 will not be met if no governance mechanism is installed that ensures a fair effort sharing, taking into account infrastructure requirements. Alternatively, it is possible that the target will be met, but only through efforts in countries where renewables are strongly supported by local policy instruments, e.g. in Germany or Denmark. In the end, this solution would be far from cost-effective and would render climate and energy policy in Europe very costly.

Acknowledgments

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Appendix

See Appendix Table A1, A2, A3 and Fig. A1.

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Chapter 5

Strategies against shocks in power systems - an analysis for the case of Europe *

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Strategies against shocks in power systems – an analysis for the case of Europe

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Electricity systems are constantly exposed to geopolitical, techno-economic and natural uncertainties that may endanger security of supply. Therefore, it is crucial that policy makers concerned about it consider a variety of possible futures that cover the range of these uncertainties – and not only the one that is perceived as the most likely. In particular, they should account for the possibility of sudden shocks in their decisions with the goal of making the system more "robust". However, long-term power system models which are an important pillar of policy decision making are typically designed to determine the cost-minimal power system for a specific expected future; such a system is not necessarily the most robust one. By combining the classic investment optimization approach with the tools of Robust Decision Making we analyze the viability of different strategies that may potentially increase the robustness of a power system. For the case of the European power system we pursue a dedicated analysis with the European power system model LIMES-EU. Based on a total of more than 40,000 model runs, we find that strategies promoting the ability of countries to always produce at least 95% of their electricity demand domestically significantly help to reduce the loss of load in case of shocks. Such a strategy is not cost-optimal for the expected future without shocks; but the additional costs (about 0.1% of total system costs) are low compared to the benefits of significantly increasing the power system's robustness.

Highlights:

- We analyze the performance of different strategies against shocks in power systems
- We apply an investment optimization model in combination with Robust Decision Making
- For the case of Europe, we test the performance of strategies with 40,192 model runs
- We find that pure cost-minimization does not result in the most robust power system
- Additional national reserve capacities increase the system's robustness significantly

Abbreviations: CCS – Carbon Capture and Storage; CSP – Concentrated Solar Power; NTC – Net Transfer Capacities; PV – Photovoltaic; RDM – Robust Decision Making; VOLL – Value of Lost Load

1. Introduction

In order to decide on new energy policies, decision makers frequently rely on scientific advice (European Commission, 2014a; IPCC, 2014). An important pillar of this policy advice consists of long-term energy scenarios based on numerical optimization models that inform about the cost-efficient future development of today's power systems (Chiodi et al., 2015). The calculation of a cost-optimal investment pathway is based on an expected development of external parameters such as fuel prices and investment costs. Though their future development is uncertain, possible deviations from the expected future are often neglected, for example in the European Commission's Impact Assessments (European Commission, 2014a, 2011). But with the electricity system being constantly exposed to geopolitical, techno-economic and natural uncertainties, it is crucial to design the system in such a way that it performs well under a variety of possible futures – not only the one that is perceived as the most likely. In this context, sudden short-term shocks that do not allow for an adaptation of the capacity stock are particularly challenging. Policy making based on studies that disregard the possibility of shocks may lead to serious vulnerabilities of the electricity system and – given the various uncertainties about the future – may actually not be as cost-efficient as the studies suggest.

So what are viable strategies, beyond pure cost-minimization, for ensuring that an envisioned power system also performs well under shocks? This question addresses the issue of energy security, an aspect typically not considered in long-term optimization models but prominently covered both in policy debates and scientific literature. Energy security is a multi-faceted issue with various different definitions and indicators depending on the respective context.[1] In the Global Energy Assessment energy security is defined as the "uninterrupted provision of vital energy services" (GEA, 2012). In line with this definition Cherp and Jewell (2011) discern three different perspectives of energy security: robustness, resilience and sovereignty. The concept of robustness stems from a technological point of view on the danger of technical failures and natural disasters; resilience refers to broader societal attributes such as the ability to build and increase the capacity for reorganization and adaptation (Anderies et al., 2013; Walker et al., 2004); sovereignty covers political concerns about foreign dependency. In this paper we focus on robustness, which can more generally be defined as a reduced sensitivity of output to shocks (Anderies et al., 2013). Reaching robustness implies diverging from the strategy that would be optimal in the case of absolute certainty, and instead engaging in a strategy that yields near-optimal outcomes for a large variety of possible futures (Rosenhead et al., 1972).

In order to determine which strategies are viable to increase the robustness of power systems against shocks, we combine the classic optimization approach of power system planning with the tools of Robust Decision Making (RDM) (Lempert et al., 2006). According to RDM a system is considered to be robust when it performs well for a large variety of possible futures. We consequently analyze how a cost-minimal power system that is determined by a typical optimization model performs under shocks and compare its performance with systems based on different design strategies other than pure cost-minimization, namely increased fuel diversity, self-sufficiency and redundancy, as well as excess transmission and storage expansion. Focusing on the case of Europe, our analysis is based on more than

[1] See Månsson et al. (2014) and Winzer (2012) for reviews of different energy security indicators

40,000 model runs with the long-term power system model LIMES-EU. We thereby focus on large-scale shocks that could possibly affect the entire European power system and cover shocks on both thermal and RES-based[2] power generation, on the transmission system, as well as on the fuel supply. Though we focus on Europe, the tools we use are applicable to other regions of the world. The findings we draw from the case of Europe turn out to be rather general in nature and are therefore also of interest to non-European energy policy makers.

In the following section, we provide an overview of existing tools for decision making under uncertainty and elaborate on our approach in more detail. We also describe the strategies and shocks considered in our analysis of the European case. The robustness of the power systems resulting from the different strategies is assessed in Section 3 and our conclusion is presented in Section 4. In the appendices, we provide a general overview of the applied optimization model LIMES-EU (Appendix A) and state the model equations for implementing the strategies (Appendix B).

2. Method

Our analysis focuses on the possibility of low-frequency, high-impact events. The rarity of these events complicates the task of ensuring energy security as the majority of the established risk management tools are not applicable (Nepal and Jamasb, 2013). The following subsection presents existing tools for decision making under uncertainty and motivates the application of Robust Decision Making in our context. In Section 2.2 we describe our approach in more detail. Section 2.3 presents the strategies considered in our analysis of the European power system and Section 2.4 provides an overview of the shocks that we analyze.

2.1. Existing tools for decision making under uncertainty

There is a large variety of tools designed to account for risks and uncertainties about the future in energy sector investment decisions, system planning and policy making (cf. Andrews, 1995; Hickey et al., 2010; Zeng et al., 2011). The applicability of individual approaches depends on the level of knowledge, i.e. whether there is risk, uncertainty or ignorance. In the case of risk, both the possibility and the probability of future states are known; under uncertainty – sometimes also termed “deep uncertainty” – only the possibility is known; and ignorance exists when even the possibility of events is unknown (cf. Stirling, 1994).

Stochastic tools are widespread in order to account for political and fuel price risks in individual investment decisions.[3] For overall system planning, the use of deterministic approaches is more common but has been repeatedly criticized and the importance of a variety of scenarios has been

[2] renewable energy sources

[3] Such risk management tools include two-stage models (Bistline and Weyant, 2013; Hu and Hobbs, 2010; Usher and Strachan, 2012; van der Weijde and Hobbs, 2012), real-options analysis (Agusdinata, 2008; Fuss et al., 2012; Kettunen et al., 2011; Yang et al., 2008) and portfolio theory (Fuss et al., 2012; Vithayasrichareon et al., 2009).

stressed (McDowall et al., 2014; McJeon et al., 2011; Wachsmuth, 2014). Recent literature that discusses risk and uncertainty in light of policy making includes Pye et al. (2015) and Watson et al. (2015). Most influential is the work by Awerbuch et al. (2003; 2007; 2006), who apply portfolio theory for policy planning. The use of portfolio theory in the electricity sector is highly contested, however, because of the existing technological restrictions and high transaction costs compared to assets that are purely financial (cf. Hickey et al., 2010).

In addition, all probability based stochastic approaches have an important caveat when it comes to the consideration of shocks: As shocks are low-frequency phenomena it would be rather difficult to assign meaningful probabilities (Nepal and Jamasb, 2013). Furthermore, they would only have a small impact "on the average", but they have a high impact if they occur (Gorenstin et al., 1993). It is therefore important to analyze each future scenario separately (Meristö, 1989) and assume uncertainty rather than risk. Beyond that, Stirling (1994) points out that we are not able to anticipate every possible contingency and outcome affecting the electricity sector, and it is therefore ignorance that dominates real electricity investment decisions. However, the assumption of ignorance would preclude any numerical analysis of possible futures which could provide meaningful insights. We therefore reduce the strict necessity of knowing about *all* possible future states and assume that the viability of a strategy under uncertainty is a good indicator for the strategy's performance in the real world that offers shocks not deemed possible beforehand.

In order to evaluate the viability of different strategies, we rely on the concept of robustness (Rosenhead et al., 1972). The aim is not to find the optimal decision for an expected future, but rather to find a robust strategy that performs reasonably well across many scenarios. The concept of robust decisions has been extensively covered in electricity sector literature (Burke et al., 1988; Gorenstin et al., 1993; Linares, 2002). Specifically, Hallegatte (2009) highlights the need for robustness in a world of uncertain climate change. A useful approach to decide on a robust strategy is the framework of Robust Decision Making (RDM) by Lempert et al. (2006), which we adopt for our analysis and explain in the following section.

2.2. Making the RDM framework operable with LIMES-EU

The RDM framework is especially designed for decisions under uncertainty. The decision of interest here is the choice of a policy strategy that results in a robust power system, i.e. a system that performs well for a large variety of possible future shocks.

RDM consists of a process in which the decision maker first suggests candidate strategies and tests their performance for a large variety of possible futures. An indicator for the performance of a strategy is the regret, i.e. the additional costs of the strategy compared to the best strategy for a specific future (Savage, 1954). Candidate robust strategies perform well for most of the considered shocks, i.e. they have a relatively low regret over all analyzed possible futures compared to other strategies. Lempert et al. (2006) propose the upper-quartile regret as an indicator for selecting the candidate robust strategy. However, such candidate strategies may have serious vulnerabilities (i.e. high regrets) for individual shocks. In case such vulnerabilities exist, the characteristics of the futures for which the candidate

robust strategy is vulnerable are analyzed in more detail in order to design possible hedging options. Such options could be new or refined strategies or combinations of strategies that promise to be more robust. Performance of those strategies under the considered futures is subsequently assessed by additional model runs.

In the following, we describe our application of the RDM approach in this paper for the case of Europe. In order to identify strategies that are robust against possible shocks to the European power system, we analyze the impact of a variety of such shocks on different future systems, each being the result of a different political strategy. Our analysis of shocks is focused on prospective power systems of the year 2030, as this is currently the most relevant year for strategic energy policy decisions in the EU. In order to facilitate our analysis, we apply the model LIMES-EU (Nahmmacher et al., 2014). The long-term investment model for the electricity sector of Europe is designed to determine cost-efficient investment pathways and dispatch decisions for the European electricity system in 10-year steps from today until 2050 (see Appendix A). Our analysis is focused on the year 2030, but using a model that spans until 2050 allows us to take into consideration the long-term decarbonization targets envisioned by the European Commission and repeatedly emphasized by the European Council (2011, 2009). We apply LIMES-EU both for identifying the optimal investment pathways under different political strategies and for assessing the impact of short-term shocks on the respective systems. This is done in two consecutive steps:

1. *Strategy outcome in reference future.* In a first step we identify candidate strategies and determine for each one the hypothetical power system in 2030 that would result from pursuing the respective strategy (strategy outcome). The default strategy is pure cost-minimization without additional considerations; more dedicated strategies include, for example, provisions for higher fuel diversity. For each of the strategies an investment path is determined by optimizing the future power system for a single reference future without shocks. The strategies will obviously result in different power systems with different infrastructure investment costs. An overview of the considered strategies is provided in Table 1; they are described in more detail in Section 2.3.
2. *Introduction of shocks.* In a second step we expose the power systems to a variety of possible future shocks using 2030 as the year of analysis (see Section 2.4). The investments determined in the first step are fixed now, meaning that shocks may lead to a different dispatch, a failure in meeting the electricity demand and/or a failure in meeting the emission target. In order to compare the performance of the different systems under shocks, the lost load is translated into costs by factoring in a value of lost load (VOLL). Emissions are capped by default, but in the case of shocks, it is possible to exceed this cap in order to reduce the loss of load.[4] Those excess emissions are not associated with further costs, as we focus on energy security in this paper.

Based on the strategies' policy costs determined in the first step (i.e. their additional costs compared to the default strategy of pure cost-minimization) and their performance under shocks in the second step,

[4] This is reflected by changing the standard emission constraint equation *Emissions ≤ Cap* to *Emissions ≤ Cap + X* and assigning high costs to every unit of *X* in the objective function. However, this is only done to implement the possibility of excess emissions in the model. The costs resulting from excess emissions are afterwards excluded from the total system costs and not considered in our analysis.

we calculate their regrets in comparison to the other considered strategies and then follow the framework of RDM in order to assess which strategy leads to the most robust power system.

2.3. Description of the candidate strategies

Except for the default strategy of pure cost-minimization, the strategies considered in our analysis are derived from common energy security indicators found in the literature: diversity, self-sufficiency, redundancy, flexibility and interconnectivity.

Diversification is the most popular strategy against an unknown future, especially in the case of ignorance (Bazilian and Roques, 2008; Helm, 2002; Löschel et al., 2010; Ranjan and Hughes, 2014; Skea, 2010; Stirling, 1994): "No matter how great the resources, nor how complete the knowledge, nor how sophisticated the decision making process, only fools put all their eggs in one basket" (Stirling, 1994). *Self-sufficiency* is also a prominent strategy for increasing energy security as it limits third party influence on the system (cf. Molyneaux et al., 2012; Roege et al., 2014; Stirling, 2010; Turton and Barreto, 2006). Spare capacity or *redundancy* could reduce the threat from "unplanned surges in demand or the loss of electricity from any one source" (Molyneaux et al., 2012). *Flexibility* (e.g. in the form of storage capacities) also increases the operational options in case of shocks (Roege et al., 2014; Stirling, 2010). The regional integration of electricity markets via increased *interconnectivity* may add to security of supply, too, but it also exposes the system to additional threats (Nepal and Jamasb, 2013). Molyneaux et al. (2012) therefore choose to exclude interconnectivity from their set of indicators. We account for the possibility of both positive and negative effects by both analyzing transmission expansion as a strategy and covering the break-down of transmission lines in our shock analysis.

For our analysis, the strategies are implemented in LIMES-EU as follows: The diversity strategy is modeled in two different ways, namely as an upper limit on the share in annual electricity generation per primary energy carrier ("generation-based") or as a constraint on the share in available capacity respectively ("capacity-based"). Though self-sufficiency is often referred to as the dependence on foreign supply of primary energy carriers, we only concentrate on the final good electricity in our analysis and model self-sufficiency as a minimum constraint on annual electricity production from national or regional power plants. Redundancy is implemented as a constraint that at every point in time supply capabilities must exceed a certain threshold in relation to actual demand. Flexibility is reflected by an increased installation of storage capacities and interconnectivity by a further expansion of the international transmission network. For a more formal description of the strategies, see Appendix B, where we present the model equations that were added to LIMES-EU in order to implement the different strategies.

Table 1: Strategies

Strategy	Description	Geographical scope*
Default	Pure cost-minimization	-
Diversity (generation-based)	Diversified generation mix	national / regional / Europe
Diversity (capacity-based)	Ability of diversified generation mix	national / regional / Europe
Self-sufficiency	Minimum constraint on domestic generation	national / regional
Redundancy	Excess generation capacities	national / regional / Europe
Interconnectivity	Expansion of transmission capacities	(national)
Flexibility	Expansion of storage capacities	national / regional / Europe

* national – strategy valid for each country separately; regional – strategy valid for each regional group of countries separately ; Europe – European-wide strategy

Table 1 provides an overview of the strategies considered in our analysis. We model different levels of each strategy (e.g. different levels of storage expansion) and analyze their viability separately. In addition, some of the strategies may be valid for every single country separately, for overall Europe on aggregate or for regional groups of countries. Regional initiatives for increased cooperation with regard to a safer and more economic operation of the power system already exist today (Umpfenbach et al., 2015) and are becoming ever more important with the European Commission and the Council promoting regional cooperation in their recent decisions about the 2030 climate and energy framework and the Energy Union concept (European Commission, 2015a, 2014b). For the strategies based on regional cooperation, countries are grouped according to Figure 1. The chosen grouping is based on ENTSO-E's regional groups with additional subdivision of the former UCTE-area into Iberia, Eastern Europe, Southeastern Europe and the remaining central European countries.

Figure 1: Grouping of countries to regions. There are seven strategy regions: Central Europe, Eastern Europe, Southeastern Europe, Baltics, Iberian Peninsula, British Isles and Fennoscandia.

2.4. Description of the shocks considered

In order to test the strategies' suitability for enhancing the robustness of the future European power system, we test how the resulting systems respond to a variety of possible future shocks. We thereby focus on large-scale shocks that could possibly affect the entire European power system. We cover shocks on both thermal and RES-based power generation, on the transmission system as well as on the fuel supply. Specifically, we consider the following four types of shocks: (i) a heat wave changing the

availability of thermal power plants and hydro-based generation units; (ii) a break-down of international transmission corridors; (iii) long periods of low infeed from wind and solar power plants; and (iv) a shock to the fuel supply (gas, hard coal, biomass) reflected by changing prices and/or a drop in the overall quantity supplied. The exact kind and strength of each shock are again subject to variation and are to be covered by multiple separate model runs. All shocks are modeled to last for one month. The shocks are assumed to be unexpected and can therefore not be considered in previous dispatch decisions, for example by filling storages in order to prepare for the shock. The following paragraphs describe the individual shocks in more detail.

2.4.1. Heat wave

The impact of climate change and extreme weather on the electricity sector is extensively covered in the literature. High water temperatures decrease the efficiency of thermal power plants that use river cooling or even require their temporary shut-down (Förster and Lilliestam, 2009; Hoffmann et al., 2013; Klein et al., 2013; Koch et al., 2014; Linnerud et al., 2011; Pechan and Eisenack, 2014; Rübbelke and Vögele, 2010; van Vliet et al., 2013). In southern Europe, hydro power plants are likely to be affected negatively by climate change, while northern European hydro stations could profit from higher mean temperatures (Lehner et al., 2005; van Vliet et al., 2013). The regional assumptions on the size of the impact on hydro stations and thermal power plants with steam turbines are based on the results in van Vliet et al. (2013) that provide a detailed analysis for the European countries under different scenarios of climate change. The generation capacities in southern Europe are most vulnerable to rising temperatures: According to van Vliet et al. (2013), Spain and Bulgaria might face a drop of 20% in available thermal power production capacities. In Portugal, the availability of hydro power might fall by nearly 30%.

2.4.2. Transmission break-down

The transmission system is a critical infrastructure of large-scale power systems that is exposed to a variety of possible shocks. Accidents or terrorist attacks on transmission lines may cause severe supply interruptions (Bompard et al., 2009); extreme weather such as storms or icing poses an additional threat particularly to overhead transmission lines (Schaeffer et al., 2012). The break-down of a single line could lead to cascading events with consequences for the entire power system (Crucitti et al., 2004). However, the representation of such cascading consequences is beyond the scope of the applied power system model. We focus our analysis of shocks to the transmission system on the break-down of individual international transmission corridors, which is implemented as a decrease in cross-border net transfer capacities (NTC). If there is only one transmission corridor (or substation) existent between two countries today, a shock reduces the respective NTC to zero; in the case of more than one corridor or substation, we also model a partial loss in NTC.

2.4.3. Low electricity production from wind and solar power

Long periods of low wind and solar infeed might seriously challenge the future European power system, but their possibility is often disregarded in long-term energy system models (Plötz and Michaelis, 2014). For our assumptions on particularly low availability of wind and solar power plants, we analyze a 33-year

European weather dataset (ECMWF, 2012). Out of this dataset, we select the worst weeks of wind power, the worst weeks of solar power as well as the worst weeks of an aggregate of both wind and solar power.[5] For each of these three time series (wind, solar and aggregate), we retrieve the worst week for every country as well as the five worst weeks for Europe as a whole. Each of these weeks is modeled as a separate shock (lasting one month) with the wind power shock for an individual country incorporating the correct historic wind and solar situation of that specific week for the other countries.

2.4.4. Fuel supply shock

A further threat to the European electricity system stems from the high dependence on primary energy carriers. Many European countries rely on imports for fossil fuels (EUROSTAT, 2015, 2014). While there is a global market for coal with a large diversity of suppliers, the supply side of natural gas is highly concentrated. The dependence on a few suppliers and unstable political relations to some of them threatens the security of supply for natural gas both in terms of price and quantity. In addition, the gas supply network is based on a few major pipelines, which makes it a possible target for terrorists (Lilliestam, 2014). We consider gas supply shocks in terms of prices that rise to up to 300% of the expected price as well as in terms of quantity, for which we model a drop in fuel supply from Russia of up to 100%. The supply of biomass also incorporates uncertainties with regard to prices and quantities: The market for biomass is characterized by local suppliers and by the high weather dependency of biomass yields. Price shocks are considered to up to 200% of expected prices, and quantities may decrease to 25% of demand. Due to the global availability of hard coal, a shock in the supply of hard coal is only modeled as a price shock (with prices rising to up to 200%).

3. Results

In this section, we present for the case of Europe how the different future power systems that each result from a different design strategy perform under short-term shocks. Based on their performance we select the most viable strategy (Section 3.1) and compare the characteristics of this best performing power system with the default power system that results from pure cost-minimization (Section 3.2). For each of the strategies presented in Section 2.3 we analyze a set of sub-strategies that differ in their target level, for example the level of diversification. Overall, we analyze the performance of 157 different power systems under 256 different shocks[6], resulting in a notable number of 40,192 model runs.

3.1. Performance of prospective systems under shocks

In the model LIMES-EU, shocks may lead to a different dispatch, a loss of load, excess emissions and consequently different system costs. The effect of the modeled shocks in terms of lost load, excess

[5] The joint assessment of both wind and solar power is pursued with a weighting factor of 2/3 for wind power and 1/3 for solar power.

[6] including 5 heat wave shocks, 85 transmission shocks, 102 wind and solar shocks, 35 gas supply shocks, 24 biomass supply shocks, 4 coal supply shocks and one model run without any shock

emissions and overall costs is depicted in Figure 2 for each of the considered strategies. The strategies are sorted along the vertical axis; there are a total of 157 different sub-strategies resulting in 157 different power systems. The performance of the different power systems under shocks is depicted along the horizontal axis, with each black dot representing a strategy-shock combination. The blue dots represent the upper-quartile value of the shocks' impact for each strategy.

Figure 2a shows for each strategy the effect of the shocks on the lost load; it indicates that the strategies promoting redundancies in the capacity stock are the only ones capable of considerably increasing the security of supply (i.e. reducing the lost load). As these strategies limit the lost load, it is understandable that they in turn lead to the highest amounts of excess emissions (Figure 2b). In order to jointly assess all impacts caused by the shocks, we translate the lost load into costs by factoring in a value of lost load (VOLL). We next sum up all costs, including the electricity generation costs and the costs for lost load as well as the investments and fixed costs needed for realizing each strategy.

Figure 2c presents the costs of each strategy-shock combination by stating its regret, i.e. the additional costs compared to the cost-minimal strategy for that same shock. The results shown in Figure 2c are based on an assumed VOLL of 10€/kWh which is in line with estimates in current literature (de Nooij et al., 2007; Reichl et al., 2013; Welle and Zwaan, 2007). As the actual VOLL depends on a variety of different factors and varies considerably in the literature, we also calculated the regrets for other levels of VOLL (see Appendix C). Though the absolute regrets strongly depend on the chosen VOLL, the relative performance of the strategies and the overall result do not change: Except for the redundancy strategy, none of the considered strategies are significantly more robust than the strategy of pure cost-minimization.

Based on the upper quartile regret, we determine the best target level for each strategy.[7] Figure 3 shows the regrets of these selected power systems; this time only in comparison to the other selected systems. An analysis of the figure again highlights the viability of additional reserve capacities. The strategy promoting redundancy on a national basis has the lowest upper quartile regret (7.5bn$€_{2010}$) and does not involve significant vulnerabilities (i.e. shocks with high regrets). We therefore conclude that this is the most robust strategy. Its target level of guaranteed national generation capabilities is just 95%, meaning that the electricity to serve peak demand does not have to be provided from national power plants completely. However, under the default strategy of pure cost-minimization, only 7 of 29 model regions are reaching the target level of the robust strategy. The fact that the national strategy is more robust than the regional or European-wide one defies the popular result of many power system optimization exercises that a complete Europeanization of the national power systems is desirable. In fact, the national redundancy strategy can be interpreted as a national self-sufficiency strategy, with the difference that the self-sufficiency strategy implemented for our analysis requires actual domestic generation instead of the weaker "capability" for domestic generation promoted by the redundancy strategy. In the following section, we analyze the characteristics of the most robust power system in more detail.

[7] We also tested the median and maximum regret as indicators for the choice of the best strategy parameter, but the upper quartile regret turned out to be the most appropriate.

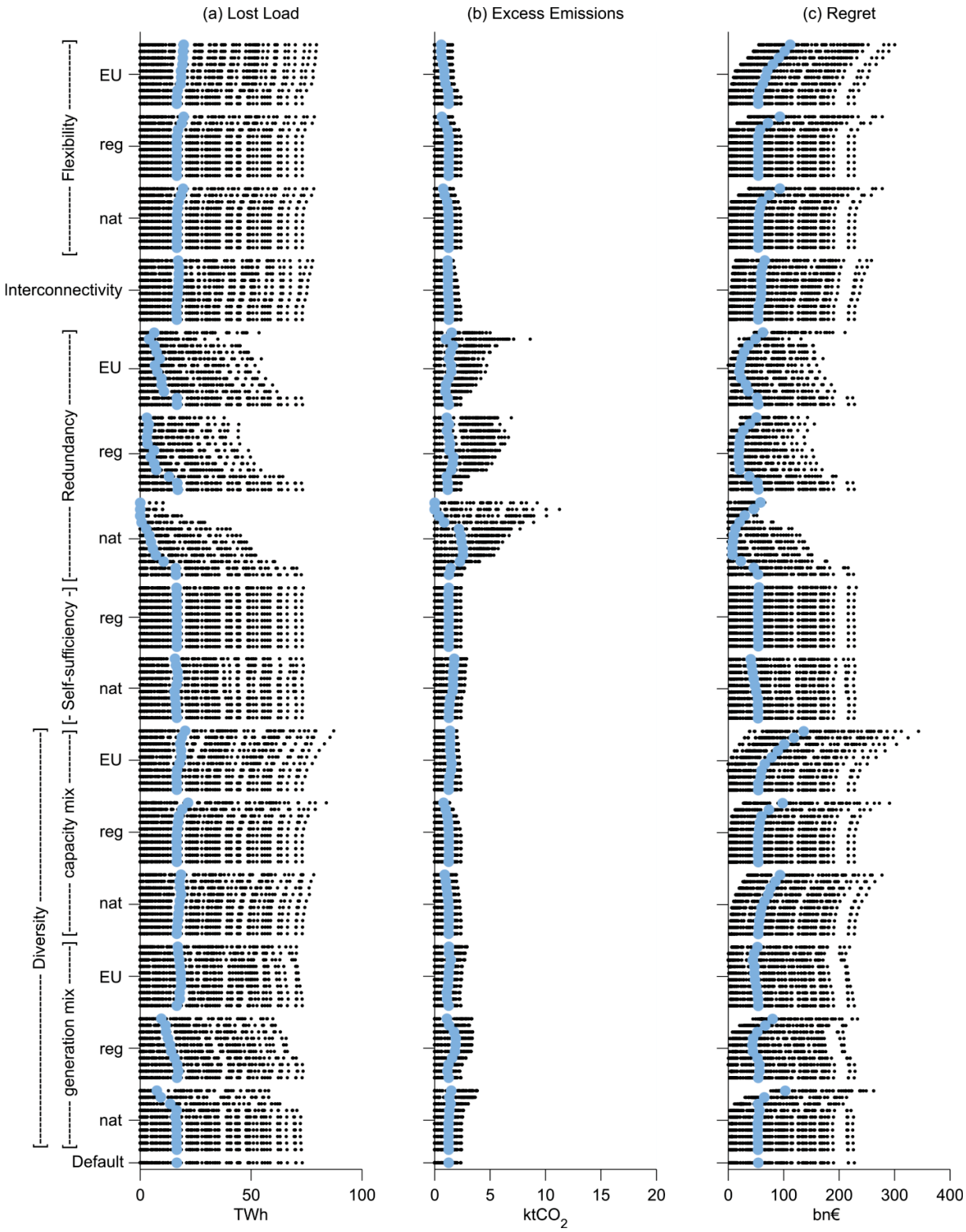

Figure 2: Lost load (a), excess emissions (b) and regret (c) of all considered sub-strategies (vertical axis). The blue dots show the upper quartile value for each strategy.

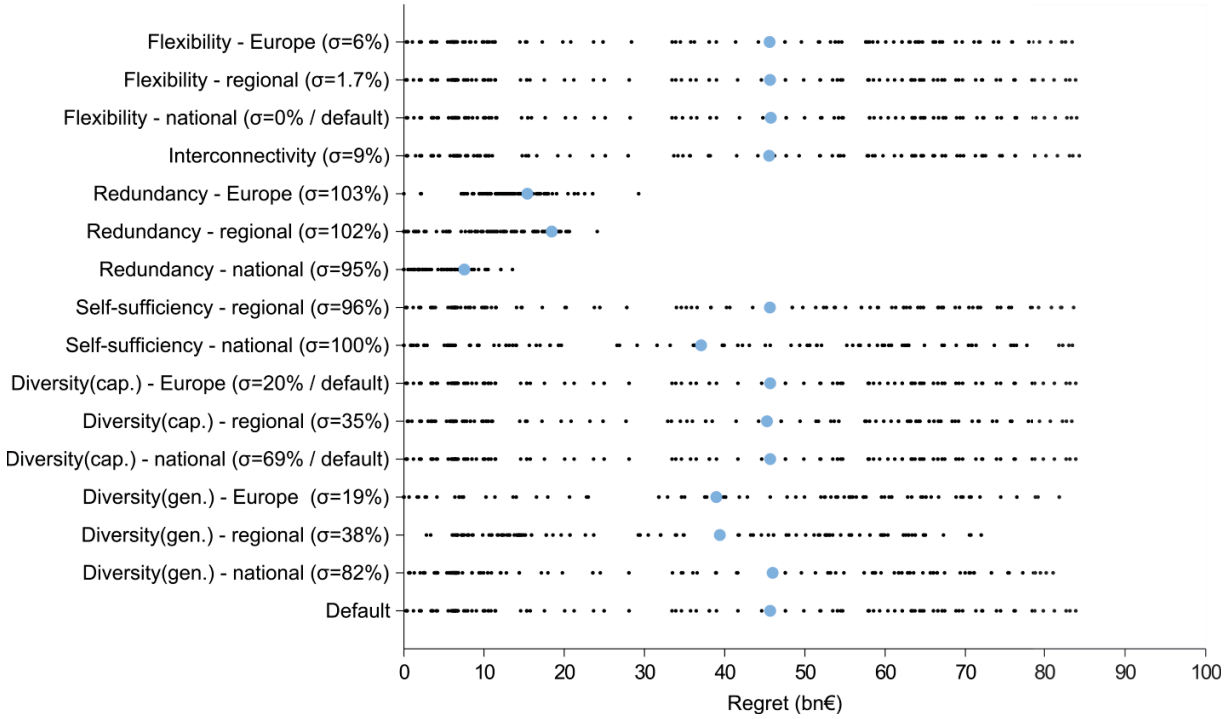

Figure 3: Regret of the strategies with the best target level. The blue dots show the upper quartile regret for each strategy.

3.2. Characteristics of the robust power system

Though the robust strategy seems to highlight the benefits of national electricity provision, the general export-import pattern does not change considerably. In Figure 4, we compare the relation of national electricity generation to national electricity demand for every country under the default strategy (horizontal axis) and the robust strategy (vertical axis). Each dot represents a country: Dots below the dashed line indicate that the respective countries reduce their domestic electricity generation under the robust strategy; dots above the dashed line indicate an increase in domestic generation. Overall, there are only minor changes in the export-import pattern. The import-export patterns are more balanced under the robust strategy but still far from being equal across countries. For the most part, importing regions under the default strategy remain electricity importers under the strategy promoting additional national generation capacities. Lithuania experiences a strong decrease in exports, but due to its size, this has only a small effect on the overall European power system.

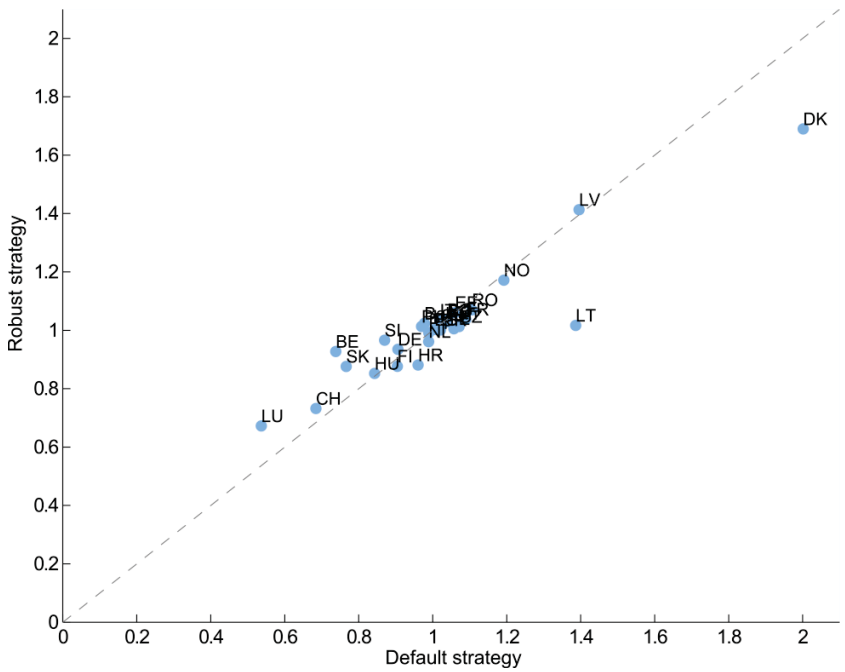

Figure 4: Relation of domestic generation to demand for the default strategy (horizontal axis) and the most robust strategy promoting national generation capabilities (vertical axis). Each dot represents a model region; the labels are based on the region codes of standard ISO 3166-1.

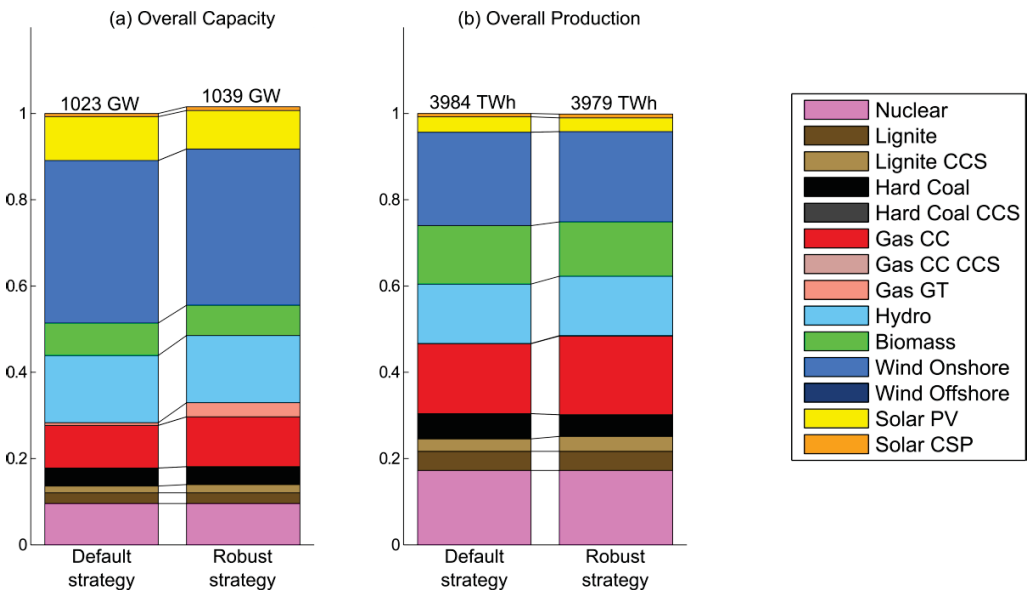

Figure 5: Capacity (a) and generation (b) mix of Europe as a whole for the default strategy and the most robust strategy promoting national generation capabilities. The vertical axes are normalized to the absolute value of the default strategy.

The robust strategy results in more national generation capabilities but it does not lead to a shift towards more domestic RES deployment. Local resource potentials and transmission costs remain the leading decision parameters for new RES capacities. The strategy does decrease European-wide share of RES by two percentage points, though. As Figure 5b shows, the missing supply is substituted by electricity generation from natural gas combined cycle power plants. In order to still meet the emission reduction target, the deployment of carbon capture and storage (CCS) increases slightly, while power generation from hard coal without CCS decreases. But the main difference between the robust system and the one resulting from pure cost-minimization is in the capacity mix. Figure 5a shows a strong increase in gas turbines from only 6GW to 33GW. Their additional capacities are the main effect of the robust strategy. If there is no shock they are virtually not used at all. But as typical peak power plants with low investment costs, they are a meaningful way to ensure electricity supply in the case of shocks and to increase the security of supply.

Pursuing the robust strategy results in only little additional costs: The discounted costs until 2030[8] are about 1.2bn€$_{2010}$ (0.1% of total system costs) higher than for the default strategy of pure cost-minimization – in case there is no shock. These additional costs are very low compared to the benefits of a robust power system: In the case of a shock, the strategy may save up to 85bn€$_{2010}$.

4. Discussion and conclusion

We combined the application of a long-term power system model with the tool of Robust Decision Making in order to analyze whether the classic optimization approach results in a robust power system or if additional strategies beyond pure cost-minimization are needed to increase the system's robustness against shocks. We considered large-scale shocks on different parts of the power system, comprising the fuel supply, the failure of international transmission lines, a reduced output of wind and solar power plants, as well as a reduced availability of thermal and hydro power plants. Starting from established energy security indicators, we analyzed the performance of strategies resulting in an increased diversification of electricity generation, national self-sufficiency, the build-up of excess generation capacities and the expansion of transmission and storage capacities. We modeled an implementation of the strategies on a national, regional or system-wide level. Though we pursued our analysis in Section 3 on the European power system, the chosen approach as well as the considered strategies and shocks are deliberately designed to be applicable to many other regions of the world.

The two main results we draw from our analysis are: (i) Of the strategies tested, only additional national reserve capacities significantly increase the system's robustness and (ii) the effect of such a strategy is largely limited to the capacity mix; generation as well as international trade patterns change only slightly. In the following paragraphs we discuss these results as well as the applied method in more detail.

[8] Over the whole time span of the model, i.e. until 2050, these costs increase to about 15bn€$_{2010}$ or 0.7% of total system costs.

The results of our analysis indicate that the default approach of pure cost-minimization – as typically applied in LIMES-EU as well as many other long-term power system models – may not lead to a power system that is sufficiently robust against shocks. Also, only a few of the additional strategies we tested turned out to be effective in improving the system's performance under shocks – though all could potentially increase a system's energy security index. More specifically, only the strategies that require a build-up of additional generation capacities are truly capable of reducing the lost load in the case of shocks. Other strategies, such as those promoting an increased expansion of transmission or storage capacities or a further diversification of the generation mix, do not seem to be effective in significantly improving the system's robustness. However, this finding might be specific to the European case – a system that is (with regional exceptions) already fairly diversified and interconnected. Consequently, an assessment of strategies in regions with low initial diversification and interconnectedness may turn out to be very different.

The strategy that is most viable for increasing the future power system's robustness promote the build-up of national reserve capacities and enables countries to always provide 95% of their electricity demand domestically. In contrast, regional or even European-wide strategies are not that effective; the build-up of an international reserve capacity does not yield the most robust system. This is remarkable as investment optimization models typically highlight the efficiency of a further integration of national power systems (Fürsch et al., 2013; Hagspiel et al., 2014; Schmid and Knopf, 2015). The recent Energy Union package of the European Commission also promotes enhanced regional cooperation and the solidarity among neighboring countries (European Commission, 2015a).

However, it is only at first sight that our results contradict the ambition of a stronger integration: The suggestion that countries should provide (ex-ante) for their energy security on a national basis does not imply that regional cooperation is not beneficial if a shock actually occurs. In fact, the effect of the national strategy is primarily limited to the capacity mix, which shows a strong increase of gas turbines. The generation mix is not much affected by the national strategies, though the share of fluctuating RES decreases slightly in favor of dispatchable gas-fired combined cycle power plants. As gas turbines are characterized by low capacity costs and rather high operating costs, they are ideal as a back-up in case of shocks, but are hardly used in ordinary situations. As is the case without the national strategy, wind and solar power plants are installed where their resource potential is most abundant and the international transmission grid is further expanded. The countries' import-export patterns do not differ greatly from the system based on pure cost-minimization; in both cases the international electricity trade is significantly more pronounced than today, which supports the position for a further integration of the European electricity system.

So why are national reserve capacities more viable than a European-wide reserve? The national strategies result in a distribution of reserve capacities over the whole continent, which obviously helps in case of shocks if the continent is not a copperplate. However, if international transmission capacities were high enough, a European-wide reserve capacity might have economic advantages: The required overall capacity could be lower in case shocks do not happen simultaneously over the whole continent and the capacity could be composed of otherwise decommissioned power plants in countries with over-capacities. We did not model any combinations of strategies, but it is likely that the combined strategy

of a European-wide reserve capacity and a stronger transmission expansion has significant disadvantages in case of a transmission shock.

The assessment of potentially viable strategies was limited by the scope of the chosen power system model. In fact, there are promising strategies both on the supply and on the demand side of the power sector that could hardly be reflected in any long-term power system model. For instance, additional LNG terminals may be a promising hedge against uncertain gas supply via pipelines, but the transport infrastructure for natural gas is usually not part of power system models. However, the preclusion of LNG infrastructure expansion might be acceptable as this strategy is too focused on a single kind of shock, and the goal of our analysis was to find general strategies against a multitude of different shocks. The non-consideration of demand side measures is another relevant point; inelastic demand is a central assumption of most long-term power system models. For our analysis we assumed a fixed VOLL of 10€/kWh. If demand were at least partially elastic, some supply shocks may be significantly less costly. In fact, this point is also stressed in the recent public consultation on a new energy market design (European Commission, 2015b).

This hints at the fact that RDM frameworks require the development of the conceptual approach and respective models to go hand-in-hand. While we have added to the literature with respect to the former, we have also identified important gaps with respect to the latter. Ensuring the availability of national excess capacities is a plausible strategy against shocks, but more analyses of strategies that are difficult to implement in common power system models are still needed.

Acknowledgements

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Appendix A: Description of LIMES-EU

LIMES-EU is a linear optimization[9] model that simultaneously determines cost-minimizing investment and dispatch decisions for generation, storage and transmission technologies that are needed in order to serve the future demand for electricity and to comply with future energy and climate policies. Its integrated approach together with an intertemporal optimization until 2050 allows for analyzing consistent and cost-efficient pathways for the future development of the European power system – both on aggregate and on national level.

[9] The model is formulated in GAMS and uses the linear solver CPLEX. http://www.gams.com

The model version applied in this paper comprises 26 of the 28 EU Member States[10] plus Switzerland, Norway and the Balkan region. Except for the Balkan region, all countries are represented as individual model regions. The model is calibrated to the base year 2010, for which installed power generation and storage capacities are fixed according to Platts (2011) and EUROSTAT (2013). The installed transmission network is reflected by the NTC summer values of 2010 as reported by ENTSO-E (2013).

In order to accommodate both long-term investment decisions and short-term fluctuations of wind, solar irradiance and demand, LIMES-EU makes use of two different time scales. The long-term scale ranges from 2010 to 2050 and is subdivided into 10-year time steps. Investment decisions are optimized for each time step. The short-term scale subdivides the time steps into multiple time slices. Eight time slices - with a length of three hours each - add up to one representative day. A weighting factor is given to each representative day; together they add up to one model year. Assigning different weights to representative days allows a representation of days with both common and rare load patterns. In this paper, we work with a total of 56 time slices per year. The balancing of electricity demand and supply, i.e. the dispatch of generation, storage and transmission capacities, is modeled for each time slice.

There are 14 different generation technologies modeled in LIMES-EU. The vRES technologies wind onshore, wind offshore, solar photovoltaic (PV) and concentrated solar power (CSP) are intermittent with their availability varying both on a spatial and temporal scale. To account for intra-regional differences in wind and solar resources, each model region is subdivided into three resource grades per intermittent generation technology. Dispatchable technologies in LIMES-EU comprise lignite, hard coal, natural gas combined cycle power plants and gas turbines, as well as nuclear, biomass and hydro power plants. Electricity generation based on lignite, hard coal and natural gas is associated with CO_2 emissions. Optionally, those power plants can be enhanced with carbon capture and storage (CCS) technology that reduces their CO_2 emissions by storing them underground.

Transmission is modeled as a transport problem from the center of one region to the center of a neighboring region – with the maximum transmissible amount of electricity being restricted by the installed net transfer capacity (NTC). The transmission of electricity between model regions is associated with losses. Network constraints and transmission losses within a region are not explicitly modeled in LIMES-EU (’copperplate’ assumption).

Two different storage technologies are available in LIMES-EU: intraday and interday storage. While intraday storages can only shift electricity provision between time slices of the same day, interday storages are able to shift electricity provision between all time slices of the same year. Compared to intraday storage, interday storage is subject to higher investment costs and higher storage losses.

See Nahmmacher et al. (2014) for a detailed description of the various technologies represented in LIMES-EU.

[10] excluding Malta and Cyprus

Appendix B: Model equations for strategies

In this section, we state the model equations added in order to implement the discussed strategies. Only the country-specific strategies are stated; for the regional or EU wide strategies, the requirements are summed up over the respective model regions.

Table B.1: Description of symbols

	Symbol	Description
Indices	t	years
	τ	time slices
	r	regions
	te	electricity generation technologies
	cn	transmission connections
	st	storage technologies
	pe	primary energy types
Sets	TE_{pe}	all electricity generation technologies working with pe
	CN_r	all transmission connections of region r
Parameters	$d_{t,\tau,r}$	electricity demand (time slice specific)
	$\bar{d}_{t,r}$	average electricity demand
	l_τ	length of time slice τ
	$\alpha^a_{r,te}$, $\alpha^{ts}_{\tau,r,te}$	availability factor (annual, time slice specific)
	σ^{div}, σ^{dom}, σ^{red}, σ^{conn}, σ^{flex}	strategy parameters
Variables	$G_{t,\tau,r,te}$	electricity generation
	$K^G_{t,r,te}$, $K^{CN}_{t,cn}$, $K^{ST}_{t,r,st}$	installed capacity (generation, transmission, storage)
	$\Delta K^G_{t,r,te}$, $\Delta K^{CN}_{t,cn}$, $\Delta K^{ST}_{t,r,st}$	new capacity (generation, transmission, storage)

Diversity (generation-based) is modeled as an upper bound on the share of a primary energy carrier in overall regional electricity generation.

$$\sum_\tau l_\tau \sum_{te \in TE_{pe}} G_{t,\tau,r,te} \leq \sigma^{divG} \sum_\tau l_\tau \sum_{te} G_{t,\tau,r,te} \qquad \forall t, pe, r$$

Diversity (capacity-based) is modeled as an upper bound on the annual available generation capacity working with a respective primary energy carrier relative to annual regional demand.

$$\sum_\tau l_\tau \sum_{te \in TE_{pe}} \alpha^a_{r,te} K^G_{t,r,te} \leq \sigma^{divC} \sum_\tau l_\tau d_{t,\tau,r} \qquad \forall t, pe, r$$

Self-sufficiency is modeled as a lower bound on annual domestic electricity generation relative to annual regional demand.

$$\sum_\tau l_\tau \sum_{te} G_{t,\tau,r,te} \geq \sigma^{dom} \sum_\tau l_\tau d_{t,\tau,r} \qquad \forall t, r$$

Redundancy is modeled as a lower bound on available generation capacity relative to regional demand.

$$\sum_{te} \alpha^{ts}_{\tau,r,te} K^{G}_{t,r,te} \geq \sigma^{red} d_{t,\tau,r} \qquad \forall t,\tau,r$$

Interconnectivity is modeled as a lower bound on transmission capacity relative to average regional demand.

$$\sum_{cn \in CN_r} K^{CN}_{t,cn} \geq \sigma^{conn} \bar{d}_{t,r} \qquad \forall r$$

Flexibility is modeled as a lower bound on storage capacity relative to regional peak demand.

$$\sum_{st} K^{ST}_{t,r,st} \geq \sigma^{flex} \max_{\tau}\left(d_{t,\tau,r}\right) \qquad \forall t,r$$

Appendix C: Performance of strategies as a function of VOLL

Figure C.1 illustrates that the absolute regrets strongly depend on the chosen VOLL. However, the relative performance of the strategies and the overall result do not change: Only the strategies promoting redundancies in the capacity stock (green lines) have upper quartile regrets that are considerably below that of the default strategy.

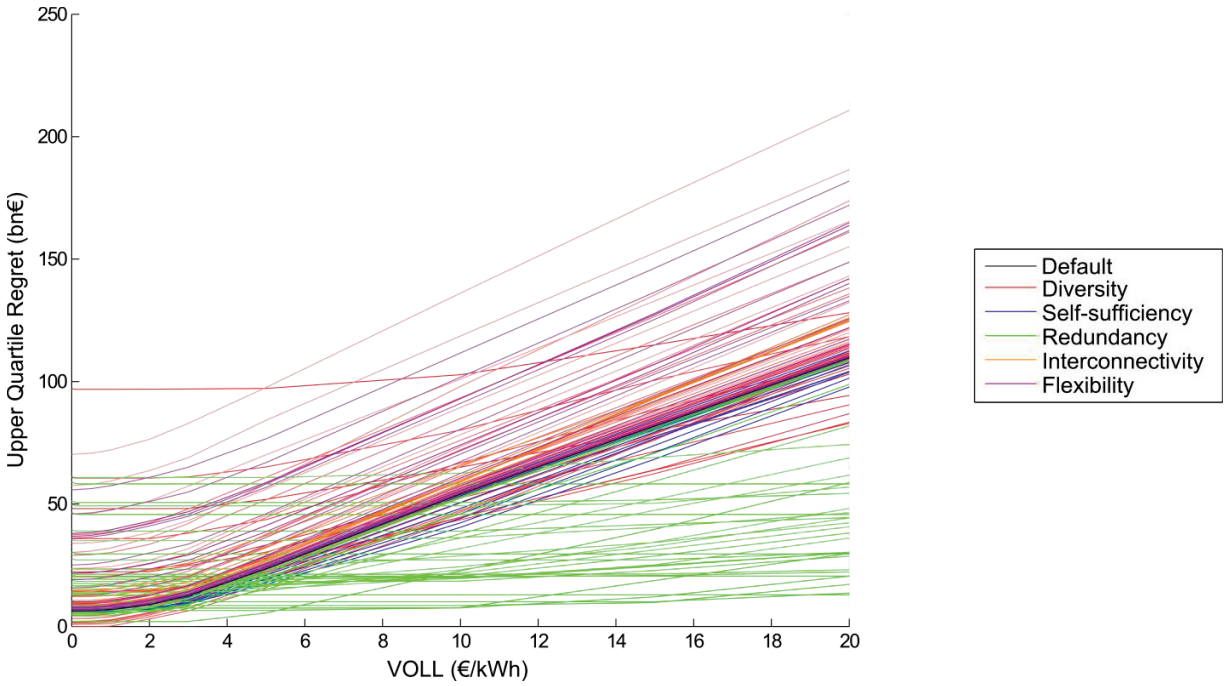

Figure C.1: Upper quartile regret of the strategies as a function of VOLL. Each line represents a strategy with a different regional scope and target level. For the ease of interpretation, the strategies are grouped into the categories of promoting diversity, self-sufficiency, redundancy, interconnectivity or flexibility.

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Chapter 6

Synthesis and outlook

1. Overview

This thesis addresses research questions about the modeling and the analysis of long-term strategies for the future European power system with a focus on the year 2030. In particular, the aim of this thesis is to contribute both to the academic and public discourse about RE targets and infrastructure needs, and to the methodological advancement of power system models by focusing on two major aspects: (i) the modeling of the European power system with high shares of RE and (ii) the analysis of the 2030 power system under uncertainty.

The first aspect is mainly covered by Chapters 2 and 3 that provide a transparent description of the investment optimization model for the European power system LIMES-EU with a special focus on a novel approach to improve the representation of the temporal variability of electricity demand and VRE availability. The analyses performed with regard to the second aspect are all based on LIMES-EU and are the subject of Chapters 4 and 5. Chapter 4 analyzes the cost-optimal future European generation mix for a variety of different scenario assumptions. A special focus is put on the role of RE in the future generation mix and the costs of a RE target that is higher than optimal. Next to an aggregate European analysis, the chapter also includes an analysis of the cost-optimal RE expansion on national level. In contrast to studying optimal power systems for different futures, Chapter 5 is concerned with the determination of a robust power system that performs reasonably well for a variety of possible futures. In particular, the chapter analyzes the performance of different power systems under short-term shocks.

The following section summarizes the results of the core chapters in the overall context of the thesis. Section 3 discusses the main findings and the use of the model LIMES-EU as a methodological basis of this thesis. Section 4 points to selected issues worth further research.

2. Synthesis of results

The thesis consists of four core chapters. In the following paragraphs, I describe their individual contribution to the overall subject of the thesis.

Chapter 2 presents the methodological basis of this thesis: the model LIMES-EU. The scenarios on the future European power system that are analyzed in the succeeding chapters are all drawn from this model. It is based on the LIMES modeling framework which allows for generating consistent scenarios on the cost-efficient future development of power systems. LIMES simultaneously optimizes investment and dispatch decisions for generation, storage and transmission technologies in an intertemporal way. In order to answer the research questions of this thesis, LIMES-EU includes updated and revised input data, new model equations as well as a revision of the geographical scope and resolution. The model comprises 26 of the 28 EU Member States[1] plus Switzerland, Norway and the Balkan region. Except for the Balkan region, all countries are represented as individual model regions in order to analyze both

[1] excluding Malta and Cyprus

national and aggregate European results. To provide transparency, Chapter 2 gives a detailed overview of the model's underlying assumptions, its input data and a full list of the model equations.

Despite the model's long-term focus until 2050, LIMES-EU effectively accounts for the short-term variability of electricity demand and the VRE sources wind and solar. Similar to other long-term power system models, the operation of generation, storage and transmission technologies is only modeled for a small set of representative situations in LIMES-EU. Selecting representative days for power system models is not obvious though: Only a few days can be included in the model as solving time increases with temporal resolution; but an inadequate choice of days potentially distorts model results. **Chapter 3** describes a novel approach for selecting representative days that is applied to input data for LIMES-EU. Unlike most existing approaches, its automated and computationally efficient design makes it suitable for input data with a large number of different fluctuating time series (i.e. multiple different VRE technologies and/or regions). A validation of the approach with LIMES-EU shows that a small number of model days developed in this way are sufficient to reflect the characteristic fluctuations of the input data. While too few model days lead to biased results with higher VRE shares and an underestimation of total system costs, already six model days are sufficient to obtain reliable results. The transparent description of the approach that is based on Ward's established clustering algorithm (Ward, 1963) ensures its reproducibility and the possibility of applying it on input data for other power system models.

With the features described in Chapters 2 and 3, LIMES-EU is capable of generating future scenarios on the European power system that are both technically feasible and economically viable. In light of the EU's recent decision on an energy and climate policy framework from 2020 to 2030 (European Council, 2014), **Chapter 4** provides an analysis for the electricity sector on the cost-optimal RE share in 2030 that is consistent with the long-term decarbonization pathway until 2050. In addition to the analysis for Europe on aggregate, there is a detailed analysis on the effect of a cost-optimal RE expansion on the individual European countries. Caused by the unequal resource availability, the optimal RE deployment differs strongly across countries with significant effects on the countries' electricity trade balance and international transmission needs. In contrast to the European Commission's official impact assessment of the 2030 policy framework (European Commission, 2014), the scenario analysis pursued in Chapter 4 explicitly accounts for uncertainties about future techno-economic developments such as fuel prices and investment costs. It turns out that the cost-optimal RE share varies considerably across the studied scenarios, namely between 43% and 56%. With 49%, the share stated in the impact assessment accompanying the European Commission's proposal for the energy and climate policy framework until 2030 (European Commission, 2014) is well within this range. But given the large uncertainties, it is possible that a future RE target for the electricity sector is set higher than the cost-optimal level. Next to an analysis of the cost-optimal share, Chapter 4 therefore provides an analysis of the additional costs of a non-optimal RE target. Though large additional costs may occur before 2030 when setting a target that is higher than the cost-optimal share, the long-term costs are likely to stay below 1% of total discounted system costs over the period 2011–2050.

Even though scenario analysis is an established method for studying the impact of different assumptions about the future on the optimal generation mix, it has an important weakness for system planning

under uncertainty: Each model run gives the optimal investment pathway for an expected future, but it remains unclear which of these investment pathways to choose in the end. Instead of analyzing optimal investment decisions for an expected future, **Chapter 5** is therefore concerned with determining a robust power system that performs reasonably well for a large variety of possible futures. In particular, by combining LIMES-EU with the tools of Robust Decision Making (Lempert et al., 2006) for a total of more than 40,000 model runs, the chapter analyzes the viability of different strategies (such as fuel diversity, transmission expansion or excess generation capacities) to increase a future system's robustness against short-term shocks. Chapter 4 showed that a cost-optimal RE expansion would result in a stronger integration of the European electricity system and would make some countries importing a large share of their electricity demand from foreign power plants. Notwithstanding, Chapter 5 emphasizes that strategies promoting the capability of countries to produce at least 95% of their electricity demand domestically significantly help to increase the robustness of the European power system. The strategy only refers to the capability, though: With additional gas turbines being the main effect of such a strategy, its impact is largely limited to the capacity mix. The generation mix and international trade patterns remain very similar to the cost-optimal ones determined in Chapter 4.

3. Discussion

The long-term investment model for the European electricity system LIMES-EU constitutes the methodological basis of this thesis. In the following, I discuss the benefit of using optimization models for power system analysis in general and the suitability of LIMES-EU in particular. Section 3.2 reflects from different perspectives on the added value of the results presented in this thesis.

3.1. Discussion of the method

The analyses pursued in this thesis are concerned with scenarios on the future of the European power system. Due to its size and complexity, computer-based models – in particular optimization models – are an important means to facilitate such analyses. Before discussing the specific features of LIMES-EU, it is worthwhile to reflect on the use of optimization models in general.

Investment optimization models generate cost-optimal investment pathways for a given set of assumptions about the system and about the future development of exogenous parameters. As it is impossible for a model to incorporate the entire characteristics of the European power system with all its complexity and uncertainties, the scenarios resulting from optimization models should not be understood as predictions of the future. This is not the aim of optimization models that do not mean to simulate the world as closely as possible but abstract from existing regulations, market failures and the irrationalities of human behavior. The benefit of analyzing scenarios for the future European power system that are based on optimization models is different: By determining cost-optimal investment pathways they can (i) show if a political target (e.g. with regard to CO_2 reduction) is technically feasible given the assumed technology options and (ii) give a benchmark with regard to the cost-optimal configuration of the future system and its costs. This system will most probably not materialize but its analysis generates useful insights, e.g. about the value of different technologies. In order to not give a

false impression of certainty, it is important to transparently state the simplifications inherent to the model and the uncertainty in assumptions about the future.

The model LIMES-EU and its input assumptions are transparently documented in Chapter 2 of this thesis. The model is designed to appropriately reflect the central features of the European power system which are necessary to generate scenarios that are both economically viable and technically feasible. It is calibrated to adequately represent the countries' local resource availabilities and electricity demand levels. The explicit representation of load and VRE variability and the implementation of the basic flexibility constraints of thermal power plants ensure the technical feasibility of the scenarios. The economic viability of technology options is determined by further taking into account their efficiencies, investment costs, fuel prices and other cost factors such as maintenance costs.

When developing a model, deliberate and transparent decisions have to be taken on which aspects to include and which to exclude – based on the research question at hand. Most of these decisions imply a trade-off between computation time and the accuracy of representation. An important part of model development is therefore the development of approaches that help to reflect real-world characteristics in a computational efficient way. For instance, an approach applied in many long-term power system models is the use of net transfer capacities (NTC) between model regions to represent the transmission system. NTCs allow for roughly estimating the need for overall transmission capacity expansion between countries. For LIMES-EU, the drawback of not being able to obtain more detailed results with regard to individual national or international transmission corridors has an important benefit: The simplified representation allows for a simultaneous optimization of investment and dispatch decisions for generation, transmission and storage technologies for several model regions in an intertemporal way from 2010 to 2050. Only this simultaneous optimization ensures that the model results are consistent across technologies, regions and time.

For the development of the model version LIMES-EU, a special focus has been put on an efficient representation of the temporal variability of electricity demand and VRE availability. As the model is applied to analyze decarbonization scenarios that potentially incorporate large shares of VRE, accounting for their specific characteristics was a necessary condition for the model. With the approach described in Chapter 3 of the thesis, it is possible to effectively cover the characteristic fluctuations of electricity demand and VRE availability across 29 model regions with as few as six representative days. Established approaches are not capable of condensing the information of such a large number of time series this efficiently.

With its novel approach to represent the variability of wind and solar power, its simultaneous and intertemporal optimization of generation, transmission and storage capacities until 2050, and its country-specific calibration and resolution, LIMES-EU is a qualified model to analyze the research questions addressed in Chapters 4 and 5 of this thesis. The model solves fast enough to allow for an in-depth consideration of uncertainties, which is a core aspect of the analyses in Chapters 4 and 5: In the latter, a sub-model of LIMES-EU is solved more than 40,000 times in order to analyze the impact of shocks to the European electricity system.

3.2. Discussion of selected results

The work presented in this thesis includes valuable results with regard to the modeling of power systems with high shares of RE and the analysis of the cost-optimal future development of the European power system with an explicit consideration of uncertainty. This section discusses to which extent these results add value beyond the scope of this thesis.

With regard to power system modeling, the thesis emphasizes the importance of adequately representing the temporal variability of VRE in models. For doing so, Chapter 3 presents a computationally efficient approach that is applicable to all kinds of power system models optimizing dispatch only for a limited number of representative situations. The method is especially suitable for models with multiple fluctuating time series, for which appropriate approaches were missing so far. The detailed documentation of the approach in Chapter 3 enables its applicability to other models. In fact, transparent documentation is an important aspect of this thesis in general and much effort has been put into openly stating the relevant assumptions inherent to the model LIMES-EU. The model documentation in Chapter 2 includes all relevant model equations and input data – not only for scientific reasons but also to allow interested modelers to adapt individual features for their models.

With regard to the analysis of the future European power system, some valuable findings of political relevance can be drawn from this thesis, in particular with regard to the future RE expansion in Europe. The analysis in Chapter 4 shows that due to the different resource availability across Europe a cost-optimal European RE expansion would imply very different national RE expansion needs. So far, the European target for 2030 has not been broken down to national targets. But when the national expansion targets were stipulated in the context of the European target for 2020 (European Parliament and European Council, 2009), this was not done according to local resource availability but rather based on the national GDPs and existing RE capacities. If RE expansion is intended to happen more cost-efficiently in the future, policy makers should think about an effort sharing mechanism that ensures that RE capacities are installed were they are most cost-efficient. To reach this end, increased European cooperation and a stronger interconnection of the European electricity system are needed. Nevertheless, despite the benefits of producing the electricity were RE availability is most abundant, Chapter 5 shows that countries should maintain a high level of domestic generation capacities. The countries' capability to serve a major part of their electricity demand by national production significantly increases the system's robustness against short-term shocks.

A general finding of this thesis with regard to both the modeling and the analysis of future power systems is the importance of appropriately considering the uncertainty about future developments. Chapter 4 illustrates that the optimal configuration of the European power system in 2030 is very sensitive to particular parameter assumptions. In addition, Chapter 5 shows that when considering the possibility of short-term shocks, a robust power system looks different from a cost-minimal power system optimized for a deterministic future. Based on these results, modelers may want to consider the permanent implementation of methods to account for core uncertainties in their analyses in order to draw robust results from optimization models. The importance of considering uncertainty is also of relevance to policy makers and regulators. With the optimal configuration of the European power

system varying strongly across possible futures, it may not be wise to base important energy policy decisions on a single study that only focuses on one specific expected future, such as the impact assessment for the 2030 policy framework (European Commission, 2014).

4. Further research

The ongoing decarbonization of the European electricity system will continue to create societally important research questions in the years to come. As the analyses in this thesis showed a high sensitivity of results to changes in input assumptions, uncertainties about the future should be explicitly considered, wherever possible, when analyzing the optimal configuration of the future power system or the potential impact of new policies.

While numerical models are playing an important role in today's scenario analysis, it might be of great value to intensify the studying of scenarios that are based on only limited or no modeling. Technical feasibility and power system costs are not the only decisive factors in the transformation of the European power system and there is only limited possibility to reflect the complexity of real world decision making processes in power system models. For instance, an analysis of appropriate effort sharing schemes for RE investments across countries would have to take into account national preferences and technologies' potential co-benefits situated outside of the electricity system. Some aspects could be reflected by complementing model-based analyses with participatory approaches (cf. Schmid and Knopf, 2012), but others may be simply beyond the scope of power system models.

In case power system models are involved in studying the future system, aspects situated at the boundaries of large-scale power system models could be particularly interesting for further research. The benefits of representing the demand side and linkages with other sectors in more detail in power system models are motivated in the following.

In this thesis, the analyses are almost entirely concerned with the supply side of the European power system. As in most other large-scale power system models, electricity demand is exogenous to LIMES-EU and assumed to be completely inelastic. But with the rising share of VRE requiring an increasing flexibility of the residual power system, also demand side flexibility becomes more important (Lund et al., 2015). Including an elastic demand in the form of price dependent load shedding or load shifting possibilities may have a large impact on the supply side in form of reduced need for storage or peak power plants. A more detailed representation of the demand side is therefore worth studying more precisely in long-term models.

Another subject deserving further attention in power system models is the more explicit representation of linkages between the electricity sector and other sectors such as heat and transport. If the power sector contributes to decarbonizing other sectors via their electrification in a large scale, an improved representation of their characteristics is indispensable. For instance, if electricity demand for charging e-vehicles makes up a significant share of overall electricity demand, the temporal fluctuations in charging e-vehicles have to be considered in power system models: Schill and Gerbaulet (2015) show

that different modes of charging the vehicles could result in significantly different optimal electricity generation mixes. In the case of the heat sector, combined heat and power (CHP) plants have an important share in electricity generation in several European countries today. Some models account for this by a must-run constraint of these power plants. However, this approach is very simplified and may be even misleading: While a must-run constraint decreases the flexibility of the system, equipping CHP plants with thermal storages and power-to-heat devices might as well lead to a strong increase in the flexibility of the thermal power plant capacity.

Representing the demand side and linkages with other sectors in a more detailed way naturally increases the computational demand of a model. With limited computational capacity, incorporating such aspects in a large-scale model may not be possible without a less accurate representation of other aspects. Therefore, deliberate and transparent decisions have to be taken on which aspects to include and which to exclude – based on the research question at hand.

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List of individual publications

The following list provides an overview about the publication status of the four core chapters (Chapters 2 to 5) of this thesis:

- Chapter 2 is published online as: *P. Nahmmacher, E. Schmid, B. Knopf (2014). Documentation of LIMES-EU - A long-term electricity system model for Europe, Potsdam Institute for Climate Impact Research, Potsdam.*
  https://www.pik-potsdam.de/members/paulnah/limes-eu-documentation-2014.pdf

- Chapter 3 is published in a revised version as: *P. Nahmmacher, E. Schmid, L. Hirth, B. Knopf (2016). Carpe diem: A novel approach to select representative days for long-term power system modeling, Energy 112, 430-442.*
  http://dx.doi.org/10.1016/j.energy.2016.06.081

- Chapter 4 is published as: *B. Knopf, P. Nahmmacher, E. Schmid (2015). The European renewable energy target for 2030 - An impact assessment of the electricity sector, Energy Policy 85, 50-60.*
  http://dx.doi.org/10.1016/j.enpol.2015.05.010

- Chapter 5 is submitted and under review for *Energy Economics*

Statement of contribution

The four core chapters of this thesis (Chapters 2 to 5) are the result of collaborations in this PhD project between the author of this thesis and his advisors and colleagues. The author of this thesis has made extensive contributions to the contents of all four chapters, from conceptual design and technical development to numerical implementation, analysis and writing. This section details the contribution of the author to the four chapters and acknowledges major contributions of others.

Chapter 2: The author was responsible for the conceptual design, handling and writing of the chapter. The described model LIMES-EU is based on the LIMES modeling framework developed by Markus Haller, Sylvie Ludig and Nico Bauer. In order to answer the research questions of this thesis, LIMES-EU includes updated and revised input data, new model equations as well as a revision of the geographical scope and resolution. All revisions were developed and implemented by the author. Eva Schmid and Brigitte Knopf gave continuous support in all stages of this process and supervised the development of the model LIMES-EU.

Chapter 3: The author was responsible for the conceptual design, handling and writing of the chapter. He developed the approach described in the chapter and was responsible for all presented analyses. Eva Schmid and Brigitte Knopf gave continuous support in all stages from developing the research question to writing the chapter. Lion Hirth provided the input data that is used in the application of the approach and he provided helpful advice in writing the chapter.

Chapter 4: The author was responsible for the model based analysis presented in the chapter and made significant contributions to the conceptual design and writing. All achievements from developing the research question to the writing of the chapter are the product of a close cooperation between Brigitte Knopf, Eva Schmid and the author. Brigitte Knopf was responsible for the conceptual design, handling and the writing of the chapter.

Chapter 5: The author was responsible for the conceptual design, handling and writing of the chapter. He was also responsible for the model development and implementation, and for the analyses presented. The research question was developed in close cooperation with Eva Schmid, Brigitte Knopf and Michael Pahle. All of them also provided helpful comments for writing this chapter.

Tools and resources

This thesis relies on numerical modeling. A number of software tools were used to create and run the models, and to process, analyze and visualize the results. This section lists these tools and gives references for further information (all accessed on 28/11/2015).

Modeling: The optimization model LIMES-EU is implemented in GAMS (General Algebraic Modeling System) with the solver CPLEX being used to solve the linear program. The multi-run experiments for Chapter 5 were performed with SimEnv 3.11.

- GAMS: http://www.gams.com/
- CPLEX: http://www-01.ibm.com/software/commerce/optimization/cplex-optimizer/index.html
- SimEnv: https://www.pik-potsdam.de/research/transdisciplinary-concepts-and-methods/tools/simenv

Data Processing: Model input and output were analyzed and processed using the MathWorks' MATLAB version R2011b, Microsoft Office 2010, Notepad++ v6 and Inkscape 0.48.

- MATLAB: http://de.mathworks.com/products/matlab/
- Microsoft Office: https://www.office.com/
- Notepad++: https://notepad-plus-plus.org/
- Inkscape: https://inkscape.org/en/

Typesetting: The individual chapters were prepared using Microsoft Word 2010 and LaTeX 2_ε with MiKTeX 2.9 and TeXnicCenter 2.0. The pdfpages package was used to produce the final document.

- LaTeX: http://www.latex-project.org/
- MiKTeX: http://miktex.org/
- TeXnicCenter: http://www.texniccenter.org/
- pdfpages package: https://www.ctan.org/pkg/pdfpages

Literature Management: Mendeley 1.14 and Zotero 4.0 were used for literature management.

- Mendeley: https://www.mendeley.com/
- Zotero: https://www.zotero.org/

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