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Modeling low emission scenarios for the European power sector

Doctoral thesis

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Abstract

The long-term ambition for the European power sector is to almost completely decarbonize generation of electricity. There are potentially many ways of achieving this, however, assessing an optimal transition to a low-carbon power system requires the use of advanced modeling tools.

This thesis presents a collection of papers addressing various topics related to capacity expansion modeling of the European power system. The aim of the modeling is to evaluate cost-efficient decarbonization strategies. The most significant contribution of this work is the development of the European Model for Power system Investments (with high shares of) Renewable Energy, EMPIRE. This is a multi-horizon stochastic programming model where investments are optimized subject to operational uncertainty. The model simultaneously considers long-term and short-term system dynamics, in addition to short-term operational uncertainty. Inclusion of all these features is currently not used by any other capacity expansion model for the European power sector.

The papers presented here focus on the formulation and applications of EMPIRE. Essentially all the papers touch upon analysis of decarbonization pathways for the European power sector. In addition, the role of carbon capture and storage (CCS) for decarbonizing the European power sector is analyzed in one paper. In the same paper, an evaluation of support mechanisms for enabling investments in demonstration CCS projects is presented. Another topic covered is integration of global climate change mitigation strategies computed by an integrated assessment model (IAM) in a study of the European power sector. This is handled through soft-linking of the IAM called GCAM and EMPIRE. By linking top-down and bottom-up models in this way, added detail can be provided to the IAM results. One paper presents a study where capacity factors from EMPIRE are used in life cycle assessment of electricity generation technologies in Europe. Improved estimations of utilization of different generation technologies can make the LCA impact analysis more accurate.

In addition to the aforementioned topics, the thesis presents a contribution to the development of convergence improvements for the Benders decomposition method applied to large-scale power system investment planning problems. Also, a technique for improved handling of seasonal storage in power system capacity expansion models is discussed.

The modeling studies show that large-scale deployment of wind power and carbon-capture and storage is the most cost-efficient approach to decarbonize the European power sector. Intermittent power generation should be built where the production potential is highest, and the transmission system should be reinforced to be able to balance large fluctuations in renewable production. If the transmission system is not developed, CCS becomes more important in the decarbonization as less wind power can be deployed. In order to secure investments in demonstration CCS plants financial support policies are needed. Investments in solar PV are limited in these studies, suggesting that additional cost reductions are needed for the technology to become competitive without support policies.

Preface

This thesis is submitted in partial fulfillment of the requirements for the degree of Philosophiae Doctor (PhD) at the Norwegian University of Science and Technology (NTNU) in Trondheim. The research presented here has been supervised by Professor Gerard L. Doorman at the Department of Electric Power Engineering and Professor Asgeir Tomasgard at the Department of Industrial Economics and Technology Management. Funding has been provided by the Centre for Sustainable Energy Studies (CenSES), a national research center for environment-friendly energy research (FME), through The Research Council of Norway contracts 209697 and 190913/S60.

Acknowledgments

During my time as a PhD student I have had the great pleasure to meet many fantastic people along the way. Interactions with other researchers have in various ways contributed to shaping the work I have done. Everyone who has helped me out in some way, deserves a great thanks. Unfortunately, in the interest of space, only a handful of you can be mentioned.

The research presented in this thesis would not have been possible without the excellent supervision, and invaluable support, I have received from my two PhD advisors, Professor Gerard L. Doorman and Professor Asgeir Tomasgard. I would like to express my utmost gratitude to them for guiding me through this process, and especially for providing me with confidence in my own work.

I would like to thank Bjørn Bakken, for the supervision he provided me during the first years of my research, when he was leading the LinkS project for SINTEF. I would also like to thank everyone who participated on LinkS for a great collaboration, and especially for the great times during our twice annual meetings in the US and Norway.

During Spring 2013 I had the privilege to spend six months as visiting researcher at the Department of Geography and Environmental Engineering, Johns Hopkins University, under the supervision of Professor Ben Hobbs. I would like to thank Ben for his time supervising my research, and the entire group of people I got to know at DoGEE, for their fantastic hospitality. Also, I would like to thank Professor Steven Gabriel for interesting discussions, and for inviting me to sit in on his lectures on equilibrium modeling at the University of Maryland, during my time in Baltimore.

I would like to thank the ZEP Market Economics group, and Charles Soothill and Gianfranco Guidati in particular, for a great collaboration since I joined group early in 2013. Also, a special thanks goes to Evert Bouman for inviting me to contribute to his life cycle assessment research, and to Gerardo Pérez-Valdés for implementing the stochastic generation routine in EMPIRE.

Finally, I would like to express my most sincere gratitude to my incredible girlfriend Kristin Dahlhaug, who has supported me day and night in completing this thesis. Even though the final stage of my PhD project has without doubt been the toughest challenge of my life, Kristin and our son, Filip, have also made this period the best time of my life.

Prologue

This thesis disseminates my research on modeling development of European power sector, done at the Department of Electric Power Engineering at the Norwegian University of Science and Technology (NTNU). At the outset, this PhD work was part of a multi-disciplinary project called Linking Global and Regional Energy Strategies (LinkS), in the research center FME CenSES, Centre for Sustainable Energy Studies. A consortium of collaborators from SINTEF, University of Maryland (UMD), Joint Global Change Research Institute (JGRCI), Tsinghua University and NTNU, made up the team LinkS researcher. The focus of LinkS was energy and climate change and the primary goals of the project were to:

1. Bring together scientific disciplines working on techno-economic energy system modeling and public policy in direct collaboration.

2. Consolidate regional and global energy system modeling approaches used for climate change mitigation analysis.

At the time I joined LinkS in August 2010 the project had already been ongoing for one year, since its official commencement in June 2009. The consortium comprised research institutions with extensive energy systems and integrated assessment modeling expertise, and a number of pre-existing models were made available for the project (see Table 1 for an overview).

The work package my PhD research was organized under, was mainly responsible for contributing to the second of the goals listed above. The main goal was to consider how global climate mitigation strategies could provide guidelines for the development of the European power sector at a national level. To address this issue, the decided approach was to link policy scenario analysis results from the Global Change Assessment Model (GCAM) to a capacity expansion model of the European power system. The LinkS consortium already had a model of the European power sector, the EMPS, however this model is a short to medium-term power market model without endogenous investment capabilities. This feature has since been added to EMPS through an implementation of a greedy algorithm (Jaehnert et al. 2013). Regardless of development of the EMPS model, which was conducted in parallel to my research, it was decided that for the purpose of the LinkS project, a power system investment model based on formal optimization should be developed.

The modeling work ultimately led to the implementation of the European Model for Power System Investment with (high shares of) Renewable Energy, or EMPIRE for short (Skar, Doorman, and Tomasgard 2014b; Skar, Doorman, Pérez-Valdés, et al. 2016). Although the first version of EMPIRE was officially presented at the 2011 INFORMS Annual Meeting,[1] developing it into a mature modeling framework took another year and a half. This was just in time to finalize the contribution to the LinkS project, which ended in August 2013. Early in 2014 the

1. Skar, C., G. Doorman and A. Tomasgard. Long-term expansion of the European power system governed by global emission mitigating strategies. In: *2011 INFORMS Annual Meeting*, November 13–16, 2011.

Table 1: The modeling portfolio in the LinkS project in 2010

Model	Sector	Scope	Type	Institute
GCAM[a]	Energy system, agriculture and land-use	Global	Integrated assessment	JGCRI
WGM[b]	Natural Gas	Global/Regional	Mixed-complementarity	UMD
CHINA-TIMES[c]	Energy system	China	Optimization	Tsinghua
EMPS[d]	Electricity	Europe	Optimization	SINTEF

[a] Global Change Assessment Model (Kim et al. 2006)
[b] World Gas Model (Egging, Holz, and Gabriel 2010)
[c] The TIMES modeling system with a Chinese data set (Chen, Yin, and Zhang 2013)
[d] EFI's Multi-Area Power Market Simulator (Wolfgang et al. 2009)

final report, with the EMPIRE modeling documented in Chapter 8, was published (Bakken et al. 2014).

During Spring 2013, EMPIRE received attention from the Market Economics (ME) group of the European Technology Platform for Zero Emission Fossil Fuel Power Plants (ZEP). The group was tasked to investigate the role of carbon capture and storage (CCS) in a future low carbon European electricity system with high penetrations of intermittent renewables. In addition, support measures to aid deployment of demonstration CCS were to be evaluated. The ME group found that EMPIRE had the right features needed for the study, and decided to use it as the modeling tool for the project. The work took place between April and October in 2013 and resulted in a ZEP report published in November the same year (ZEP 2013).[2]

Whereas the work in the LinkS project resulted in the implementation of EMPIRE, with extensive help and fruitful discussions with members of the consortium, the collaboration with ZEP in many ways paved the way for the research results presented in this thesis. The numerous discussions with ZEP members have provided me with a valuable insight regarding different perspectives on decarbonization among stakeholders in the European power industry. Furthermore, through the work with ZEP I have gained a deeper appreciation for models as powerful tools for decision support, helping me focus not just on model development, but also utilization.

The path this PhD research project took, diverged somewhat from what I originally foresaw in the beginning. The main contribution turned out to be EMPIRE, and the modeling results it produced, rather than the integration between GCAM and EMPIRE. The latter ended up being a partial contribution. I've realized that one of the greatest advantages of doing a PhD project is the freedom and flexibility it allows for re-defining the plan along the way, based on the opportunities that arise.

2. The following link is an example of the coverage the ZEP ME report published in 2013 received `http://www.modernpowersystems.com/features/featureccs-its-now-or-never-4186482/`. [Accessed March 2016]

Contents

Chapter 1

Introduction

The threat of climate change has actuated the need for ambitious efforts to reduce greenhouse gas emissions to mitigate, or at least moderate, the damaging impact this will have. According to the IPCC, 25 % of the total 49 Gt CO_2-eq global anthropogenic direct emissions was attributed to electricity and heat production in 2010 (IPCC 2014, p.9, Figure SPM.2). For Europe, the latest European Environment Agency (EEA) greenhouse gas inventory report for the EU-28 countries shows that public electricity and heat production accounted for 26 % of the domestic emissions (Turano et al. 2015, p. 84). In other words, a significant portion of the climate change mitigation efforts will have to focus on the electricity sector. Potentially, emissions from other sectors as well, most notably transport (with a share of 14 % of the global emissions in 2010), could be addressed in the electricity sector through fuel-shifting from petrol to electricity (Lechtenbömer and Samadi 2015).[1] In 2011 the European Commission published a study of decarbonization scenarios for the energy sector in Europe, the "Energy Roadmap 2050" (EC 2011b). The long-term goals set by the Commission is to reduce domestic emissions to 80–95 % of 1990's levels, by 2050 (EC 2011a). According to the Energy Roadmap 2050 report, this entails increasing the share of electricity in the energy mix, while simultaneously decarbonizing the electricity supply almost completely. Needless to say, the way we produce and use electricity will have to change dramatically over the next decades. That will be the backdrop of this thesis.

1.1 Decarbonization of electric power

There are several advantages with electricity as an energy carrier. First and foremost, it is extremely versatile, being used for everything from powering electronic appliances to running electric motors. Secondly, it can be transported quickly, almost at the speed of light, with relatively moderate loss. Thirdly, it can be generated using several different low-carbon, or even no carbon, technologies (i.e. technologies with low or no direct emissions). On the other hand, large-scale storage of electricity is a scarce resource in today's power systems, which makes system operation a complicated process.

Generally, three categories of power generation technologies are considered as possible options for reducing the carbon intensity of electricity generation: nuclear power, carbon capture and

1. Zwaan, Keppo, and Johnsson (2013) use a full (optimization) energy system model to show that the cheapest way to decarbonize the transport sector in the long-run is through the use of hydrogen fueled cars. However, fuel-shifting to hydrogen requires infrastructure which is not in place today. This is less of a problem for electric vehicles.

storage (CCS) and renewable energy (Lechtenbömer and Samadi 2015). The challenge is that there are significant trade-offs between the technologies related to cost, complexity to integrate into the grid, safety, technology maturity and other metrics.

Nuclear power has many advantages seen from a low-carbon generation perspective. Upon construction, nuclear power plants produce large amounts of electricity with virtually no direct carbon emissions, at very low operating costs. Safety, in particular, has for a long time been a concern with nuclear power as the environmental consequences of accidents can be catastrophic. Other issues as well, such as high capital costs and complex challenges associated with fuel waste management, play a role (Joskow and Parsons 2012). Following the Fukushima accident in 2011, any hopes of a new nuclear renaissance have been effectively quelled in Europe.

Carbon capture and storage is viewed as a promising technology for transitioning the European power system into a low-carbon future. Simplistically speaking, the idea behind the technology is to generate electricity by burning fossil fuels (such as coal and natural gas), and somewhere in the process capture the CO_2 that would normally be emitted into the atmosphere. The captured carbon is then transported and stored, indefinitely. The advantage of this technology is that plants with CCS can be operated more or less as conventional plants, providing the system with operational flexibility, while the emissions are just a fraction of unabated fossil fueled generation. The European Commission has stated that CCS is a key technology for cost-effective decarbonization, EC (2013), however, due to a lack of successful demonstration projects the role of CCS as a carbon reduction solution is uncertain. The main obstacle faced by CCS is that the technical feasibility, and commercial viability, of a complete carbon capture, transport and storage chain for power generation must be proven. Currently the cost estimates for CCS are high, but these are anticipated to decrease through technology learning following deployment of demonstration projects (ZEP 2011). Exactly where the captured carbon should be stored is an open question, but it is not unlikely that offshore storage sites have to be used, and a significant transport infrastructure will then be required (Hirschhausen, Herold, and Oei 2012).

Regarding renewable generation technologies available today, wind power and solar photovoltaic (PV) are the most promising in terms of maturity, cost and availability for large-scale deployment. In terms of environmental impacts during operation, wind and solar power are perhaps the best performing technologies of all the low-carbon options. However, a complicating factor is that their generation is fluctuating, uncertain and non-dispatchable. The non-dispatchability and uncertainty poses a problem for the most fundamental objective of operating an electricity system, preserving the balance between load and generation. Unless this condition is met, failures throughout the system can occur, which in the worst case may lead to a full system break down (black out), with serious societal and economic consequences. Introducing large quantities of non-dispatchable renewables therefore requires careful planning to ensure a reliable, secure and non-interrupted supply of electricity (a good overview of important planning aspects is provided by Perez-Arriaga and Batlle (2012)). This means not just considering the installed generation capacities of various technologies, both renewable and non-renewable, and their ability to serve load, but also the transmission system's ability to effectively transfer power from where it is produced to where it is needed. The choice of technology mix, and particularly the spatial deployment of renewables, strongly affects requirements for infrastructure.

None of the low-carbon technologies completely dominate the others on all relevant metrics they can be evaluated. An optimal system design will therefore comprise a mix of technologies. As all the technologies have different characteristics their composition in a system will have operational impacts which are important to keep in mind. This calls for a holistic system analysis for studying the role of various technologies in decarbonizing the power sector. Such an approach should in addition assess the transmission infrastructure and possible emerging technologies on the demand side, such as energy storage and demand side management. Furthermore, it is appropriate for studies to adopt a market context, as supply and demand for electricity is organized in electricity markets throughout Europe. In sum, all these considerations make the issue of decarbonizing the European electric power sector complicating to address, and necessitates the use of modeling tools.

1.2 Scope

The research presented in this thesis focuses on optimization based power market modeling of carbon emission reduction strategies, at national levels, for the European power sector. The term strategies is meant to encompass the choice of investments in generation, transmission and storage capacities, and their utilization to cover demand for electricity, in response to a climate policy. In particular, the modeling aims to address how to optimize investments under short-term operational uncertainty. With ever increasing shares of intermittent renewable penetration in the power generation mix, this becomes a highly important aspect to consider.

The main topics covered are design of investment models for large-scale power systems, especially stochastic models, and applications of such models in studies of global climate policies, technology support schemes and life cycle assessment analysis. The thesis also touches upon solution methods for large-scale stochastic programming models in energy. All the analyses presented focus only on Europe, however, the modeling methodology can in principal be applied to any region with an organized power market.

There are several topics related to the research presented in this thesis, which should be acknowledged, but are not treated. In terms of modeling, the work presented here exclusively use an optimization model representing a prefect competition market setting. Equilibrium models are not covered, although these types of models are suitable for representing a wider range of market conditions (e.g. situations where actors have market power), see Gabriel et al. (2013). The current debate on future design of the European energy market, see EC (2015) and IEA (2016), is naturally of high importance for the future development of the European power sector, but this is not discussed in this thesis. Throughout the modeling presented here a perfectly integrated European power market is assumed. Furthermore, national policies for renewable energy support and capacity mechanisms, are not included.

1.3 Organization of thesis

The structure of the thesis is as follows: Chapter 2 provides a general background, and then a discussion of recent literature, for the different research topics where contributions have been made. The papers included in this thesis are discussed in context of current and relevant research literature. The chapter begins with an introduction of investment modeling for large-scale power system, particularly focusing on models developed for decarbonization studies of the European system. Then, stochastic optimization methodology applied to these types of modeling problems is discussed. Various applications of power system capacity expansion models are highlighted. This is followed by a discussion on top-down and bottom-up modeling for energy and climate policy analysis. The focus, specifically, is on soft-linking of top-down integrated assessment models and bottom-up electricity market/investment models with more refined detail.

In Chapter 3, a list of the papers and a summary of their specific individual contributions are provided. The general conclusions based on the research are discussed in Chapter 4, along with suggested further work in this field. Finally, a list of references for the first part of the thesis is given. The papers presenting the actual research are included as appendixes.

Chapter 2

Background

2.1 Modeling decarbonization pathways for the European power system

Following the liberalization of the electric power industry in Europe during the 1990s, generation of electricity has been organized through unbundled generation companies operating in power markets. As a consequence, investments in generation technologies are no longer the responsibility of, or controlled by, vertically integrated utilities. This means that any initiative for reducing emissions and promoting low-carbon technologies must come in the form of regulations and policies affecting decisions being made in a liberalized market setting. From a modeling perspective it is therefore important to represent power market dynamics and how these are affected by policies.

2.1.1 Capacity expansion models for the European power sector

From the field of mathematical programming, the capacity expansion problem concerns the optimal development of a supply chain serving some form of demand for a good (or a set of goods). The set of decision variables typically comprises both decisions about capacity investments and production decisions, which are co-optimized. Availability of various competing technologies can easily be included, and through a suitable formulation of constraints, capacity expansion models can include infrastructure requirements, resources availability, technology limitations and policies affecting the supply chain. By covering an entire sector, and using a social welfare objective,[1] the model serves as a proxy for a model of the (long-term) development of a perfectly competitive market for the good(s) in question.[2] Due to these properties, capacity expansion models lend themselves naturally as tool for electricity sector planning (Hobbs 1995). The term investment model is used indistinguishably from capacity expansion model throughout this thesis.

Formulating a power system capacity expansion model is in principal not a difficult task. Most of the aspects of mathematically describing the investment decision process and system operation are fairly well understood. Formulating a model that is computationally tractable for large-scale systems (i.e. solvable within reasonable time with numerical methods), on the

1. Under the assumption of inelastic demand a social welfare optimization problem coincides with a system cost-minimization problem.

2. The connection between a competitive equilibrium of a single commodity market and social welfare maximization is discussed in Gabriel et al. (2013). See also Gürkan, Özdemir, and Smeers (2013) for a theoretical discussion, and proofs, on equivalence between certain equilibrium models and optimization models for capacity expansion in perfectly competitive markets.

other hand, requires a great deal of simplifying assumptions, and approximations. Krishnan et al. (2015) discuss various approaches used in planning models co-optimizing investments in different types of power system assets, such as transmission and generation projects. There are virtually unlimited ways to design a model by varying approximations and simplifications, and it is therefore important that choices made reflect the purpose of the model. Some of the most important aspects for which different capacity expansions models vary are listed below:

1. Spatial resolution and network flow modeling
2. Investment time steps and time horizon
3. Temporal granularity and horizon of operational modeling
4. Operational characteristics of generation technologies
5. Uncertainty modeling

All the elements in the above list are important to consider when designing a model for assessing decarbonization strategies involving large shares of intermittent renewables. However, not all these aspects can simultaneously be modeled in detail to the greatest extent possible as this would lead to a prohibitively large optimization problem. In practice, models are either specially designed to incorporate a selected few of the above items in significant detail, or they are design to balance a selection of them.

The centerpiece of the research presented in this thesis is the **E**uropean **M**odel for **P**ower system **I**nvestments (with high shares of) **R**enewable **E**nergy, or EMPIRE. The first introduction of EMPIRE appeared in Paper A (Skar, Doorman, and Tomasgard 2014b), although the description was somewhat brief and rudimentary. A complete mathematical formulation and modeling description of the current version of EMPIRE is given in Paper D (Skar, Doorman, Pérez-Valdés, et al. 2016), which now serves as the primary reference to the model. The geographical coverage in EMPIRE is essentially the whole of Europe (with the exception of some small countries), and the spatial detail is at national levels. Cross-border exchange of electricity between countries is modeled using a transport model. Starting from a base year, EMPIRE allows for investments in new capacity every fifth year, and the typical analysis horizon used is 2050. Investments in generation capacity, interconnector capacity and storage capacity are co-optimized with system operation using a minimum cost objective. The system operation is modeled at an hourly time-scale, and the yearly operation is represented by typical days (Skar, Doorman, Pérez-Valdés, et al. (2016) model four seasons using time segments of 48 hours). For each country, generation capacity is aggregated by technology, which is modeled as generators with linear production costs, maximum output constraints and ramp limits. Unit commitment characteristics of generation, such as minimum stable levels, minimum up and down times, start up times and start up costs, are not considered. One of the key features of EMPIRE is that investments are made subject to uncertainty about operating conditions.

In the following a review is provided on how the aspects in the above list are treated in a selection of recent optimization based capacity expansion models of the European system (with the exception of uncertainty which is discussed separately in Sec. 2.1.2).

Table 2.1: Overview of (optimization) capacity expansion models for the European power sector. Abbreviations: UC – Unit commitment, UC LR – Unit commitment linear relaxation. For the strategic steps 'Single' refers to a single investment stage formulation, while 'Myopic' refers to a sequential single step procedure. The institutions where the models are developed, along with references, are provided in footnotes below the table.

Model	Spatial	Investment		Operation		Network	Generator	Uncertainty
Name	detail	Steps	Horizon	Steps	Horizon	flow	operation	
Gold standard	HV grid	1 year	2050+	Sub-hourly	Full year	AC-OPF	UC	Stochastic
COMPETES[a]	Country	Single	2020/50	Hourly	Full year/50 hrs	Transp/DC LF	Linear	Deterministic
DIMENSION[b]	Country	5 year	2050	Hourly	4 rep. days	Transport	Linear	Deterministic[*]
DSIM[c]	Sub-national	Single	2050	Hourly	Full year	Transport	UC	Deterministic
E2M2[d]	Country	Myopic	2050	Multi-hour	8 rep. days	Transport	UC LR	Stochastic
ELMOD[e]	HV grid	Myopic	2050	Hourly	18 hours	DC load flow	Linear	Deterministic
EMPIRE[f]	Country	5 year	2050	Hourly	8 rep. days	Transport	Linear	Stochastic
EMPS[g]	Country	Myopic	2050	Multi-hour	Full year	Transport	UC LR	Stochastic
LIMES[h]	Country	5 year	2050	Multi-hour	12 rep. days	Transport	Linear	Deterministic
PowerACE-EU[i]	Country	10 year	2050	Hourly	Full year	Transport	Linear	Deterministic
URBS-EU[j]	Sub-national	Single	2050	Hourly	48 rep. weeks	Transport	Linear	Deterministic

[a] Energy research Centre of the Netherlands (ECN). References: Generation expansion Özdemir et al. (2013), transmission and generation expansion Özdemir et al. (2016).
[b] EWI, University of Cologne. Reference: Richter (2011).
[c] Imperial College London. Reference: Pudjianto et al. (2013)
[d] University of Duisburg-Essen. Reference: Swider and Weber (2007)
[e] DIW Berlin. Reference: Egerer, Gerbaulet, and Lorenz (2013)
[f] Norwegian University of Science and Technology (NTNU). Reference: Skar, Doorman, Pérez-Valdés, et al. (2016)
[g] SINTEF Energy Research. Reference: Jaehnert et al. (2013)
[h] Potsdam Institute for Climate Impact Research (PIK). Reference: Haller, Ludig, and Bauer (2012)
[i] Fraunhofer ISI. Reference: Pfluger (2014)
[j] TU München. Reference: Schaber, Steinke, and Hamacher (2012)
[*] Stochastic versions exits.

There is a rich selection of models developed for capacity expansion analysis for the European power system. As most of these models are actively maintained and developed, a description of each on the basis of the items in the above list might be misleading as the models are flexible and can easily be changed to incorporate more detailed data sets, or generally improved modeling of various system characteristics (such as network flow or operation of technologies). The purpose of the following discussion is not to provide a final classification of different modeling systems based on their intrinsic features, but rather to give a snapshot overview of the state-of-the-art in optimization based capacity expansion models of the European power system to date, and the commonly used assumptions for long-term development studies. Table 2.1 shows an overview of a selection of ten capacity expansion models, in addition to EMPIRE, used for studies of the European power sector for high shares of renewable energy, and their features. The author's view of a gold standard model, with all features modeled in significant detail is also provided.

In terms of spatial detail and network flow modeling it is clear that most of the models use a national granularity and a transport model for the grid. This is used in EMPIRE and all the other models, except COMPETES,[3] ELMOD, DSIM and URBS-EU. The two latter use a sub-national spatial detail level, which allows for national grids to be represented to some degree. However, these models also use a transport formulation for the grid modeling. COMPETES and ELMOD are the only models in this overview which endogenously approximates network flows respecting Kirchhoff's Voltage Law (KVL). ELMOD uses a DC load flow formulation, while COMPETES uses a successive linear programming approach to solve the non-linear DC load flow problem with losses. The increased accuracy in network flow modeling, however, does come at the expense of added computational complexity, which is the reason why ELMOD use a myopic investment procedure and only includes a few hours (18 in total) to represent the operation over a year. A full AC-OPF capacity expansion model for co-optimizing transmission and generation investments is detailed in Krishnan et al. (2015). Not only is this model non-linear, it is also highly non-convex, which makes this an extremely challenging mathematical problem to solve. At the present such a model is only of theoretical use.

When it comes to foresight and considerations of long-term dynamics in the investment planning, three different approaches are taken in the different models, single step, multiple myopic single steps and multiple steps within a single optimization. In the single step approach there are typically two phases, one representing a period when investments are made, and a target year of operation. The focus is on the "final" (target year) design of the system, not the transition from today, as timing of investments and operation in intermediate years are not modeled. The advantage of this approach is that the operational modeling is limited to a single year, which in practice allows the models to incorporate more temporal and technological details. In the literature review, the models COMPETES, DSIM and URBS-EU were found to be set up as single step investment models.

The myopic approach is essentially a series of single step optimizations, with the aim to reflect the transition of the system. This still allows for detailed operational modeling, and the time spent on a complete model run is proportional to the number of steps taken. ELMOD, E2M2 and EMPS use this approach. The drawback of using a myopic investment planning is that optimality of the investments is only ensured for the individual steps, not over their lifetimes. As a result no guarantee of optimality can be given for the system design. The last approach, used by DIMENSION, EMPIRE, LIMES and PowerACE-EU, is to incorporate investment steps and operational years in a single operation. The advantage of such a setup is that, unlike the single

3. Two versions of COMPETES extended to handle investments are presented in the recent literature, one with endogenous generation capacity investments, and one where both generation and transmission capacity investments are endogenously co-optimized. In Table 2.1 the respective features of both of these versions are presented.

step models, optimal timing of investments can be determined, and, unlike the myopic models, optimally of the investments are considered over a longer time horizon. The trade-off is that the computational complexity of these models is highly sensitive to the detail level in operational modeling, due to the incorporation of several years in the optimization. Therefore, as a result, such models tend use representative days to model operation over a year. PowerACE-EU is an exception in this respect as it covers several investment years and models a full annual hourly operation for each.

Just a few of the investment models recently developed for the European power system include much, or any, unit commitment (UC) consideration in the modeling of system operation. However, a wide deployment of intermittent renewables does increase the need for flexibility in the system, which is exactly what can be addressed by using a UC operational model (Brouwer et al. 2014). Some studies therefore apply a capacity expansion model for determining generation investments, and then utilize a more detailed unit commitment model for analyzing the system operation (Brouwer et al. 2016).

The strong connection between investment planning and operational planning in capacity expansion models is apparent from the development of many of these models. Many of them actually started out as pure operational, or market, models, and have later been expanded to include endogenous investments. COMPETES was originally designed as a market model for analysis of strategic behavior in the European sector (Lise and Hobbs 2005).[4] EMPS was designed as a power market model used for management of large hydro reservoirs under uncertainty (Wolfgang et al. 2009). ELMOD was one of the first large-scale markets model covering most of Europe at a very detailed gird level (Leuthold, Weigt, and Hirschhausen 2012). Exceptions to this practice are DIMENSION, DSIM, EMPIRE, LIMES and Power-Ace, which are all designed from the ground up as capacity expansion models.

The challenge of seasonal storage in power system capacity expansion models

The mid-term dimension becomes a problem for models where short time segments (such as typical days) are used to model the operation over a year. This type of setting can be useful for representing seasonality of short-term dynamics, like load and renewable generation. However, planning of seasonal energy storage is difficult to get right based on a single, or a few, day(s) of a season. A common way to deal with this issue is to define energy limits for off-take from energy storage during each short-term segment (see for instance Pudjianto et al. (2013) and Skar, Doorman, Pérez-Valdés, et al. (2016)). As operational costs for the seasonal storage technologies are typically low, e.g. reservoir hydro power has virtually zero variable costs, the energy limit tend to be binding. If there is no link between typical days used to represent seasons, this approach cannot capture the value of saving energy from one season to be used in another.[5] As the energy limits are usually based on historical data, this type of modeling will not be able to show how the management strategy for seasonal storage should change according to the development of the system.

Paper C (Brovold, Skar, and Fosso 2014) propose a way to include a medium term hydro power scheduling perspective in the short-term operational modeling of capacity expansion planning, through the use of water values (WV). This approach circumvents the need to model long

4. The first version of COMPETES included several regions of the Benelux countries, and France and Germany as satellite nodes (Hobbs, Rijkers, and Wals 2004). The model was then later expanded to cover large parts of Europe, using a national detail level (Lise and Hobbs 2005).

5. On the other hand, including links between seasons for handling season storage would probably imply an overly optimistic view on storage strategies, unless multi-stage stochastic modeling was used in the operational periods to separate seasons.

segments of short-term time steps for managing the hydro reservoir, by reflecting the value of the hydro production from a given segment of a reservoir in a given season. The water values were computed using the EMPS model (Wolfgang et al. 2009).

2.1.2 Power system capacity expansion planning under uncertainty

Uncertainty is fundamental to most decision processes, and commonly arise in planning problems in the electric power industry (Hobbs 1995; Weber 2005; Conejo, Carrión, and Morales 2010). Naturally, capacity expansion planning is no way an exception in that respect. From a modeling perspective there are several ways to deal with the uncertainty and one such, widely applied, method is sensitivity analysis.

When performing sensitivity analysis, a model's response to changing input data (or assumptions) is examined, assuming perfect foresight. Such an approach provide insights about the relative importance of different parameters, and the range of the model's results as a function of the input data. The major shortcoming of sensitivity analysis is that the optimal decisions from a perfect foresight model, calculated for a given set of input data, can exhibit severe sub-optimal performance if the input data change. As such, sensitivity analysis is an inadequate tool to reflect the optimal decisions accounting for the uncertainty (King and Wallace 2012). For this purpose, methods from the field of optimization under uncertainty is more appropriate. Optimization under uncertainty is an umbrella term used for methodologies such as robust optimization, chance-constrained programming and stochastic programming (Sahinidis 2004; Bertsimas, Brown, and Caramanis 2011). This thesis will focus on the latter.

In traditional stochastic programming (SP), such as presented by Birge and Louveaux (2011), a decision process is divided into stages based on timing of the decisions relative to the information available. The setting is such that a set of decisions are made before the outcome of some relevant uncertain parameters is observed. At the time the uncertainty is resolved, another set of decisions, commonly referred to as recourse actions, are made. In some processes, information is gradually revealed, limiting the decisions at each stage to be based only on the knowledge of past outcomes and the probability distribution of future outcomes for the uncertain parameter data. These are so-called multi-stage stochastic programs. Assuming a finite number of outcomes for the uncertain parameters at each stage, the decision process can be represented by a tree where the nodes reflect decisions and branches reflect parameter outcomes. A single path from the root node to a leaf node in such a tree is called a scenario. The (perhaps) most central topic of stochastic programming is non-anticipativity. Non-anticipativity formalizes the notion that decisions cannot be based on future revelations of information, only the past and current information available. In the context of a stochastic program with a tree structure, non-anticipativity enforces that for two distinct scenarios, decisions with common ascendant nodes at a given stage will be equal, regardless of the descendants following.

The advantage of stochastic programming is the ability to explicitly account for the effect uncertainty has (or should have) on the decision process. In particular SP is a powerful framework for assessing and valuing the flexibility to respond to information which is gradually revealed, and the possibility to hedge against unfavorable outcomes (considering their respective probability). The most common formulation of stochastic programming models optimize the expected value of the objective (for instance costs) over the probability distribution of the uncertain parameters. This reflects a risk neutral attitude to the uncertainty faced in the decision making process. Risk attitudes can also be incorporated, however, this will not be discussed here. A draw-back with stochastic programming models is that they tend to become quite large and computationally difficult to solve.[6]

For power system investment models there are various ways to utilize stochastic programming to handle uncertainty. As the planning problem covers long-term and short-term decisions, it is possible to consider long-term and short-term uncertainties as well. Long-term uncertainties are usually linked to economic development, technology development and policies. This affects parameters such as demand for electricity, investment costs, fuel prices, carbon emission costs, etc. Short-term uncertainties have more to do with the system operation, such as load fluctuations, intermittent renewable generation, short-term fuel price variability, inflows to hydro reservoirs, etc. Fürsch, Nagl, and Lindenberger (2013) present a version of the DIMENSION model where investments in thermal generation capacities are made subject to uncertainty regarding deployment of renewables. This is an example of investment decisions being non-anticipative to the outcome of long-term uncertain parameters. A second example of a stochastic programming version of the DIMENSION model can be found in Nagl, Fürsch, and Lindenberger (2013), where investment decisions are made subject to uncertainty in generation from renewable energy technologies. This is an example of short-term uncertainty affecting the long-term decisions. This is similar to the approach used in EMPIRE as discussed in Paper D of this thesis. In EMPIRE investments are made subject to uncertainty in operational decisions such as load, intermittent renewable generation and generation from reservoir hydro power (Skar, Doorman, Pérez-Valdés, et al. 2016). Formulated as a multi-horizon stochastic program, see Kaut et al. (2014), EMPIRE in addition captures the long-term dynamics of the system.

Benders decomposition for stochastic programs and applications to large-scale power system capacity expansion models

For ease of the exposition, the following discussion is limited to two-stage stochastic programming models with complete recourse.[7] A cost minimization objective is assumed. Generalizations are possible, but beyond the scope of this thesis.

For linear SP models with a minimum expected cost objective, and with uncertainty described by a finite probability distribution (i.e. scenarios), it is possible to state the problem as a single linear program (LP). This is referred to as the deterministic equivalent extensive form of the SP. In this formulation, all the first-stage and second-stage variables are co-optimized subject to the complete set of first-stage and second-stage constraints. Even though highly efficient commercial software exists for solving LPs, the size of the problems can quickly become unmanageable since the number of second-stage variables and constraints is proportional to the number of stochastic scenarios used in the model. This is particularly the true for capacity expansion models as these are typically large-scale, even in a deterministic setting. However, by exploiting the structure of stochastic programming models, specialized algorithms can reduce computation times. Munoz and Watson (2015) apply a progressive hedging algorithm to a stochastic power system investment model, where both investments in transmission and generation assets are considered. Progressive hedging is an example of decomposition by scenario. Konstantelos and

6. The computational effort needed to solve a stochastic programming problem is essentially determined by the way the uncertainty is modeled. Dyer and Stougie (2006) discuss the computational complexity of solving two-stage SP problems with discretely distributed independent random variables, and find that these problems are ♯P-hard (a complexity class of counting problems for which members of a set can be determined in polynomial time, transferred to optimization problems). In practice, the size of the uncertainty set in SP is managed by utilizing scenario reduction schemes (Heitsch and Römisch 2003), scenario generation schemes (Dupačová, Consigli, and Wallace 2000), or a combination. A slightly different approach involves sampling based algorithms where an SP is approximately solved without considering the complete set of scenarios (Higle and Sen 1999).

7. Complete recourse for two-stage stochastic programs means that for ever feasible first-stage variable the set of feasible second-stage variables is non-empty.

Strbac (2015) apply a multi-cut Benders decomposition algorithm for a transmission system investment model. Another application of Benders decomposition for power system investment planning is presented in Munoz, Hobbs, and Watson (2016). In their paper, a mix of bounding techniques and an enhanced Benders decomposition algorithm is used for improving convergence rates relative to using either approach independently.

Benders decomposition for two-stage stochastic linear programs can shortly be described as an iterative procedure where supporting hyperplanes (or cutting planes) are used to develop an outer linearization of the second-stage costs as a function of the first-stage variables. The method is an example of decomposition by stage. Originally proposed by Benders (1962), the method was first applied to stochastic programming problems by Van Slyke and Wets (1969). Convergence can be shown to be finite for continuous problems, however, the convergence rate is known to be slow unless modifications are applied. Several techniques for improving the convergence of Benders have been proposed, see Zverovich et al. (2012) for a review and a computational study of a selection of these techniques.

Paper B (Skar, Doorman, and Tomasgard 2014a) presents a special implementation of the Benders decomposition method applied to EMPIRE. The algorithm presented in the paper applies a method for improving the convergence rate of Benders, using a two-phase strategy for adding cuts to the master problem. It starts by adding aggregated cuts (one cut per iteration), and then switches to generating several cuts per iteration once the estimated error hits a given threshold. This can be seen as a reverse approach to that presented by Trukhanov, Ntaimo, and Schaefer (2010), in which multiple cuts are added but then later aggregated.

2.2 Addressing specific issues using with capacity expansion models

2.2.1 Modeling carbon capture and storage in Europe

Capacity expansion models are excellent tools for investigating system development under for various assumptions and story lines. However, the aggregate system results do not have to be the main focus of a study as the models, by design, also provide detailed results, for example for investments and utilization of individual technologies. These types of results can be useful for analyzing the role and potential of different technologies for decarbonizing the power sector. In particular renewable technologies have received much attention in recent modeling work, see (Spiecker and Weber 2014; Haller, Ludig, and Bauer 2012; DNV GL 2014), but many studies considered the role of carbon capture and storage (CCS) as a low-carbon solution for reducing emissions in the power sector (Odenberger and Johnsson 2010; Capros et al. 2008). The perhaps most extensive modeling study of CCS in Europe is presented by Lohwasser and Madlener (2012). Their paper provides a literature review of costs and technological data published for CCS, and then use an agent based power market model, Hector, to analyze the deployment of CCS for a range assumptions. EMPIRE has been used for several studies by the European Technology Platform Zero Emissions Platform (ZEP) for assessing the potential of CCS for decarbonizing the European power sector (ZEP 2013, 2014, 2015). This is also one of the central themes of Paper E (Skar, Doorman, Guidati, et al. 2016).

2.2.2 Modeling support schemes for low-carbon technologies

Quantitative studies of financial support mechanisms typically either have a single project perspective, or a system perspective. Boomsma, Meade, and Fleten (2012) present a real options analysis of renewable support schemes, which is an example of the former. Böhringer, Hoffmann, and Rutherford (2006) and Nagl (2013) apply system wide models to assess the effectiveness of quantity based and price based financial support policies for promoting renewable investments in Europe. In both these papers, equilibrium models with endogenous investments, rather than optimization models, are used in the analysis. Equilibrium models have a significant advantage over optimization models when prices are explicitly used in the mathematical formulation. For both types of models, prices appear as the dual variables of supply and demand equilibrium constraints, however, for optimization models these variables are only available once the model has been solved. For equilibrium models, on the other hand, the dual variables are used directly in the formulation. In terms of support policies, optimization models can be used to represent schemes, price and quota, for which the support is given independent of the market outcome. For instance, a feed-in tariff, structured as a selling price floor for eligible producers, is difficult to represent in an optimization model as this requires an explicit use of a dual variable in the objective. A feed-in premium, designed as a support paid on top of the market price, can be included in an optimization model simply by adjusting the short-run marginal costs.

Much of the discussion on support policies for CCS has been of a qualitative nature (Groenenberg and Coninck 2008; Stechow, Watson, and Praetorius 2011). However, some quantitative studies have been done, such as Lohwasser and Madlener (2013) who evaluate investment and R&D subsidies for CCS in Europe. Their analysis apply a version of the HECTOR model where learning effects were endogenous for CCS. Two types of learning were considered, learning by researching and learning by doing. Building on the ZEP analysis provided in ZEP (2013) Paper E presents an analysis of support schemes for CCS using the EMPIRE model. In this study, two financial support schemes, investment subsidies and feed-in premiums, are evaluated on the basis of effectiveness for promoting demonstration CCS investments. In addition, emission regulations in the form of emission performance standards are tested.

2.2.3 Using capacity factors from a capacity expansion model for life cycle assessment

In life cycle assessment (LCA) of electricity generation technologies the aim is to evaluate various impacts caused by using the technologies to produce electricity. Impacts of interest include for instance climate change, metal depletion and freshwater ecotoxictiy.

The impacts of individual technologies are typically assessed on a per kWh functional unit, which is essentially the ratio of lifetime impacts to lifetime electricity production. This is analogous to how lifetime costs of a generation technology is sometimes expressed by its levelized cost of electricity (LCoE) in power system economics. In the same way as the LCoE accounts for capital costs in addition to operational costs, the per kWh functional unit accounts for impacts related to construction (and other non-operational processes). In both LCA impact analysis, and LCoE calculations, an estimation of electricity generation from a technology is needed, however, if this estimation is not based on a holistic system analysis using a power market model, errors quickly arise. As an example, considered a coal fired power plant. As a rule of thumb, coal fired power generation has typically been considered as a baseload technology, generating at more or less full capacity, excepts for when shut-down for maintenance, or experiencing failures. Under such operating conditions capacity factors of 80–90 % can be expected for coal fired power generation. However, in systems with high shares of renewable power generation, coal fired plants may experience a higher degree of cycling as the renewables are favored in the dispatch due to very low operational costs. Also, if a sufficiently high price of carbon is implemented as a climate policy, gas fired power generation may become cheaper than coal in the dispatch, which can reduce the utilization of coal fired generation. Both LCA analysis, and LCoE calculations, will therefore be more accurate if the capacity factors are calculated using a model which endogenously computes utilization based on how the technologies are actually operated in a system.

In Paper F (Bouman, Skar, and Hertwich 2016a), EMPIRE is used to compute capacity factors of generation technologies in Europe, which are then subsequently used in an LCA analysis.

2.3 Top-down versus bottom-up energy system modeling

When it comes to economic modeling of human designed systems (e.g. energy systems) for policy analysis, a distinction is usually made between top-down and bottom-up models. The two approaches are not rigorously defined, but rather explained by typical characteristics such as focus, scope and technology detail level of the modeling. Top-down models have broad economic perspectives, seeking an economic equilibrium capturing interactions and feedback effects between sectors. The geographical detail level is often regional, covering the whole world, at least for models addressing climate change mitigation. The technology detail level for supply and demand in different sectors is typically limited. Bottom-up models consider detailed technological parameters describing system units while a partial equilibrium covering a single sector, or sub-set of sectors, is sought. Interactions with other sectors is commonly ignored, or at best, estimated. Bottom-up models tend to confine the geographical scope to a single region, with either national or sub-national detail level.

In the literature discussing the divide between the two modeling approaches, top-down models are often taken to be computational equilibrium models (CGE), whereas bottom-up models are engineering type optimization models (Böhringer 1998). Another class of models typically referred to as top-down models are the integrated assessment models (IAM). IAMs have over the recent decades become the primary tool for analyzing the cost and potential of climate policies for addressing climate change. The contribution of Working Group III to the fifth assessment report published International Panel on Climate Change (IPCC) included a collection of 900 mitigation scenarios analyzed by IAMs (IPCC 2014). The major benefit of IAMs is that the models compute cost-efficient mitigation efforts using an integrated modeling framework covering the most significant sectors, such as the energy and agricultural systems, contributing to anthropogenic greenhouse gas emissions. Due to the often detail-rich modeling of different technologies in IAM these models are sometimes referred to as hybrid models in the literature (Hourcade et al. 2006).

For the purpose of the discussion following in this chapter, the term top-down model is used for integrated assessment models and partial equilibrium models covering the whole energy system. Linking of top-down and bottom-up models is to be understood as geographical and temporal disaggregation of a top-down model's output results using a bottom-up model. The process entails both disaggregation of data to be used as input in a bottom-up model, and the disaggregation which follows naturally from the bottom-up models' more detailed output results. This type of linking is usually termed *soft-linking* as it is not a properly integrated framework of the models. The top-down model is executed independently from the bottom-up model, and information flows in one direction, from top to bottom.

2.3.1 Climate mitigation scenarios

Developing *scenarios* is an integral part of the modeling process for doing climate policy analysis. These types of scenarios reflect different possible futures in terms of policies and technological development. Although the difference may seem semantic, scenarios in this context is distinct from sensitivity analysis. Whereas the latter is a type of "what-if" analysis used to explore uncertainty in the exogenous data parameters, scenarios are more fundamental to the analysis as they directly address policy implications. An extensive discussion on the topic can be found in the PhD thesis of Philip van Notten along with a meticulous definition of scenarios in the way they are typically used in energy and climate policy analyses, (Notten 2005, p. 20):

> Scenarios are coherent descriptions of alternative hypothetical futures that reflect different perspectives on past, present, and future developments, which can serve as a basis for action.

Climate change policy scenarios tend to have a climate stabilization limit as an overreaching goal. The perhaps most well-known limit is the 450 ppm atmospheric concentration of greenhouse gases by the end of the century. By staying within this limit climate models predict that the global mean temperature rise will *likely*[8] be less than 2 °C compared to pre-industrial levels (IPCC 2014, p.13, Table SPM.1). A common approach used by IAMs to achieve this is using an endogenously computed price on carbon emissions, either through an implementation of a carbon tax or a tradable permit scheme (Clarke et al. 2009).

An important source of development and modeling based analysis of energy and climate change policy scenarios is the Energy Modeling Forum (EMF) at Stanford University. Of special interest are the scenarios developed during the EMF-22 project "Climate Change Control Scenarios" (Clarke, Böhringer, and Rutherford 2009) , and the EMF-27 project "Global Model Comparison Exercise" (Weyant et al. 2014). The scenarios developed during these projects incorporate non-idealized international implementations of climate policies, reflecting that climate change policies will most likely be adopted gradually in different parts of the world. These types of scenarios in general are less efficient and more costly, but represents a far more realistic view on how climate change mitigation efforts will materialize (Victor et al. 2014).

Two of the EMF-22 scenarios are analyzed using EMPIRE in Paper A.

2.3.2 Disaggregation of top-down modeling results for the European power sector

Many of the recent bottom-up models used for decarbonization studies of the European power system include some results from top-down models. In particular, fuel prices and electricity demand are types of parameters exogenous to bottom-up power system models that can be collected from previous modeling studies applying either integrated assessment models, or full energy system models. This can be seen as soft-linking as introduced previously in this chapter. However, we will in this section focus on studies where the linking is the focus in itself.

As a result of the EMF-28 project "The Effects of Technology Choices on EU Climate Policy", several electricity system models were used to analyze optimal infrastructure requirements for different European climate policy scenarios (Holz and Von Hirschhausen 2013). All of the models used high level scenario inputs from the PRIMES model, (Capros 2013), which is a partial equilibrium energy system model covering EU-27 with national granularity. The electricity transmission system is crudely modeled in PRIMES and the more detailed electricity system models with investment capabilities, EMPS (Jaehnert et al. 2013) and ELMOD (Egerer, Gerbaulet, and Lorenz 2013), computed infrastructure development pathways with granularity levels beyond the scope of PRIMES.

Another example of top-down/bottom-up model linking in recent literature is Deane et al. (2012), who linked results from the TIMES energy model to a detailed power market model using PLEXOS.[9] Both models used data for the Irish energy system. The added detail level was hourly

8. The probability statement likely used by the IPCC refers to a confidence level of 66–100 %.

9. PLEXOS is a commercial software package for general purpose integrated energy system analysis. Both long-term investment planning, and short-term operational planning, is supported. See `http://energyexemplar.com/software/plexos-desktop-edition/` for more information. [Last accessed March 2016].

dispatch, unit-commitment and ancillary service provision results for the power sector provided by PLEXOS, which was not available from the TIMES model.

Paper A in this thesis presents a study where a capacity expansion model of the European power system, EMPIRE, is soft-linked to GCAM (Skar, Doorman, and Tomasgard 2014b). The purpose of the study was to provide an extended analysis of the European power sector results provided by GCAM for a selected number of climate scenarios. The linking procedure was designed to harmonize scenario assumptions between GCAM and EMPIRE to the greatest extent possible. This included using the same parameters describing generation technologies, the same aggregate demand for electricity at a European level, the same fossil fuel prices, the same carbon tax. In addition, constraints were imposed in EMPIRE ensuring that the power generation technology mix at a European level corresponded to the results from GCAM. Three climate policy scenarios were investigated: two stabilization scenarios, 450 ppm and 650 ppm, from the EMF-22 project (Clarke et al. 2009), and one scenario combining several policy instruments called Global202020. The latter scenario was inspired by the EU-202020 policy package and expanded to cover the whole world over several implementation stages (Calvin et al. 2014). The linking procedure shared many similarities to the approach used by Deane et al. (2012) to link PLEXOS and TIMES, however, the full adaptation of a power system investment model of Europe to global climate policy studies is unique to date.

Chapter 3

Contributions

This chapter will discuss the contributions of the PhD research presented in this thesis. The work has been documented in papers, all published or submitted for review in peer-reviewed channels. The papers are included, following this chapter, and a list of the papers is give in Section 3.1. For each paper a summery and an overview of individual conclusions are provided, along with my own contributions to each paper.

The areas of research addressed by the papers can be summed up in the following list:

- Power system expansion modeling using stochastic programming. Papers A–E.
- Improvements of stochastic programming solution algorithm. Paper B
- Integration of top-down modeling perspectives in bottom-up power system modeling. Paper A.
- Study of decarbonization pathways for the European power sector. Papers A, D, E.
- Modeling based studies of support mechanisms to drive investments in demonstration CCS technology. Paper E.
- Incorporation of power system modeling results in life cycle assessment. Paper F.

The general overarching conclusions of the collective work presented in the papers, are discussed in the next chapter.

3.1 List of papers

Paper A: Skar, C., G. L. Doorman, and A. Tomasgard. 2014b. "The future European power system under a climate policy regime." In *EnergyCon 2014, IEEE International Energy Conference,* 337–344. doi:10.1109/ENERGYCON.2014.6850446.
Summary: A bottom-up capacity expansion model of the Europe power system is used to analyze three climate scenarios from an integrated assessment model (IAM). A soft-linking procedure, harmonizing assumptions across the models, with the aim to preserve the validity of the results relative to the IAM results is described.
Conclusions: The linking procedure demonstrated a way to provide more details to aggregated IAM results using a more detailed sector model. In particular, it was shown that for a given amount of renewable generation in Europe the optimal approach is to centralize

investments where production conditions are good, and developing the transmission infrastructure to balance supply and demand. France, Great Britain, Italy Poland, and Norway were found to be good locations for wind development. In terms of transmission expansion it was shown that interconnectors going from Spain to Germany and Poland should be reinforced.
Contributions: For this work I collaborated on designing the research idea and modeling. In addition I implemented the capacity expansion model and designed the linking procedure, collected and organized input data, performed the simulations. I analyzed and interpreted the results, in collaboration with my co-authors. I was the main author of the manuscript.

Paper B: Skar, C., G. L. Doorman, and A. Tomasgard. 2014a. "Large-scale power system planning using enhanced Benders decomposition." In *18th Power Systems Computation Conference (PSCC).* doi:10.1109/PSCC.2014.7038297.
Summary: An application of the Benders decomposition is used to improve computation times for solving a large-scale power system capacity expansion model. A technique for improving the convergence rate of Benders based on cut aggregation is presented.
Conclusions: The cut aggregations scheme was shown to reduce computation times compared to the text-book multi-cut Benders decomposition algorithm. An improvement of 32 % was found in a computational experiment.
Contributions: I designed the algorithm enhancement, implemented it and ran the simulations. I analyzed and interpreted the results, in collaboration with my co-authors. I was the main author of the manuscript.

Paper C: Brovold, S. H., C. Skar, and O. B. Fosso. 2014. "Implementing hydropower scheduling in a European expansion planning model." Renewable Energy Research Conference, RERC 2014, *Energy Procedia* 58:117–122. doi:10.1016/j.egypro.2014.10.417.
Summary: The paper presents a methodology for improved handling of reservoir and run-of-the-river hydro power within a long-term European power system expansion model. Water values calculated by a power market model specialized for systems with large shares of regulated hydro power are used as resource costs to guide water utilization.
Conclusions: The new methodology for handling of hydro power in EMPIRE was shown to have a significant effect on the investment results. Less investments in run-of-the-river hydro resulted from using more accurate production data. Also, the total regulated hydro power production was reduced. The reduction of hydro power production was offset by more installed solar power production.
Contributions: The paper is a result of a Master's thesis I supervised. My contributions were the idea of the research project, guidance on implementation of the suggested method in EMPIRE, guidance on interpretation of results and commenting on the manuscript.

Paper D: Skar, C., G. L. Doorman, G. A. Pérez-Valdés, and A. Tomasgard. 2016. "A multi-horizon stochastic programming model for the European power system." Subimtted to an international peer reviewed journal, In review.
Summary: A complete presentation of the stochastic programming capacity expansion model for the European power system named EMPIRE. This paper covers the mathematical formulation of the model and illustrates its use in a decarbonization study of the European power sector.
Conclusions: The multi-horizon stochastic programming formulation of EMPIRE was discussed, and compared to similar models. The decarbonization study showed that the EU ETS price from the European reference case 2013 can drive an emission reduction of more than 80 % in 2050, compared to 2010. Unabated fossil fueled generation is displaced by

onshore wind and fossil power plants with CCS. Increasing interconnector capacities was shown to allow for higher investments in wind power capacities, however, this does not make a large impact on total emission reduction compared to a case without grid investments.
Contributions: I designed and implemented EMPIRE, and collected, and organized, input data. I designed the scenarios in the paper and performed the simulations. I collaborated on analyzing and interpreting the results and designing the stochastic scenario generation routine. I was the main author of the manuscript.

Paper E: Skar, C., G. L. Doorman, G. Guidati, C. Soothill, and A. Tomasgard. 2016. "Modeling transitional measures to drive CCS deployment in the European power sector." Subimtted to an international peer reviewed journal, In review.
Summary: A study using EMPIRE to examining the role of CCS for decarbonizing European power, and support mechanisms for driving investments in demonstration CCS.
Conclusions: The study shows that having a diverse mix of renewable energy and CCS is the most cost-effective solution to reduce emissions from the power sector by more than 80 %, relative to 2010, by 2050. The effect of not having a CCS option available are higher emissions, at a higher cost. Demonstration CCS plants are found to require some form of transitional measures to achieve market penetration. Two different financial support schemes, and a direct control mechanism in the form of an emission performance standard, are evaluated. Demonstration projects with low fuel can be successfully supported by investment subsidies. Operational support, for instance, in the form of a feed-in premium is needed for projects with high fuel costs, such as gas CCS. A strict emissions performance standard is shown to be an effective policy instrument for driving investments in CCS, however, it also causes high prices in a transitory period.
Contributions: I contributed to developing the methodology used in the paper. I implemented the policies in EMPIRE, collected and organized input data and performed the simulations. I collaborated on analyzing and interpreting the results and designing the stochastic scenario generation routine. I was the main author of the manuscript.

Paper F: Bouman, E. A., C. Skar, and E. G. Hertwich. 2016a. "Informing LCA of electricity technologies with a power market model." Subimtted to an international peer reviewed journal, In review.
Summary: Capacity factors used in life cycle assessment (LCA) of power generation technologies is computed using a capacity expansion model for the European power system. Comparison to capacity factors previously used in LCA publications, and the effect on estimated environmental impacts, are presented.
Conclusions: Capacity factors computed by the EMPIRE was shown to deviate significantly from estimated capacity factors used in previously published LCA studies. For fossil fuel technologies the effect of these results is limited to categories sensitive to construction, however environmental impacts for such technologies are mostly caused by production processes. For solar PV the capacity factors computed by EMPIRE was shown to be lower than previously estimated capacity factors. These can be used for a more accurate determination of environmental impacts for solar PV, which can affect the ranking of technologies. The use of economic models for estimating inputs to LCA studies is argued to increase the coverage and validity of results.
Contributions: I partook in discussions on the design of the methodology used. I designed the capacity expansion scenarios, performed the EMPIRE simulations and provided structured results to be used in the LCA analysis. I contributed to interpreting the results, and

I wrote some parts of the manuscript.

Additional contributions

In addition to the papers presented in this thesis, I have made contributions to other reports and papers worth briefly mentioning, during my time as a PhD student.

- Zero Emissions Platform. 2013. *CO_2 Capture and Storage (CCS) – Recommendations for transitional measures to drive deployment in Europe.* European Technology Platform for Zero Emission Fossil Fuel Power Plants. `http://www.zeroemissionsplatform.eu/library/publication/240-me2.html`.
- Zero Emissions Platform. 2014. *CCS and the electricity market: Modelling the lowest-cost route to decarbonising European power.* European Technology Platform for Zero Emission Fossil Fuel Power Plants. `http://www.zeroemissionsplatform.eu/library/publication/253-zepccsinelectricity.html`.
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Except for the last item on the list, these contributions are not peer-reviewed, and are therefore not included in this thesis. Bouman, Skar, and Hertwich (2016b) is submitted to an international journal for review, however, it did not fit the scope of this thesis as it does not apply capacity expansion modeling for the European power sector.

Chapter 4

Conclusions

The central element, binding the different parts of this research together, is the European Model for Power System Investments (with high shares) of Renewable Energy (EMPIRE). The overall conclusions which can be drawn from the presented work in essence all relate to the modeling done, and can be divided into two parts: methodology and application.

Capacity expansion modeling

The European power system capacity expansion model, EMPIRE, fills a gap not covered by similar models. The most important strength of EMPIRE is that it is a computationally tractable model covering both long-term and short-term system dynamics, while optimizing investments under operational uncertainty. The latter feature is highly important as more and more intermittent renewable capacity is installed throughout Europe. This mix of properties is enabled through the use of multi-horizon stochastic programming. Other (European) multi-period investment models presented in the recent literature are either deterministic, or stochastic, but are then designed to make myopic investments optimized in sequential steps. The main advantage of EMPIRE relative to these models is that the resulting optimal investments will be robust over a range of operating conditions, while at the same time accounting for future anticipated long-term developments in the power sector. Not only is this important when planning for integration of renewables, but also investments in other types of generation technologies, infrastructure and energy storage, as well.

As with any stochastic programming model the computational effort involved in solving EMPIRE greatly depends on the number of stochastic scenarios used for the input data. Unlike the rich set of highly sophisticated solvers for traditional linear (continuous and mixed-integer) optimization problems,[1] few commercial off-the-shelve implementations of algorithms for stochastic programming problems exist. Development of specialized algorithms for solving stochastic models is therefore still needed, and some work on this issue has been presented here. Benders decomposition, with performance enhancement through clever cut management, as shown, is a viable approach for reducing computation times. Efficient solution of stochastic models allows for more stochastic scenarios to be considered, which is important for the quality of the modeling. Another great advantage of decomposition methods is that parallel processing can be used for further improvement, enabling models to harness the power of high performance computing clusters.

1. Examples of commercial solvers for LPs and MIPs include XpressMP, Gurobi, CPLEX and Mosek.

The value of developing a capacity expansion model such as EMPIRE has been illustrated in several decarbonization studies of the European power sector. However, additional value of the model is shown through linking the model to GCAM for studying the impact of global climate change mitigation scenarios for Europe in more detail. Using models such as EMPIRE in this way can shed light on where renewable generation capacity should be built, the need for transmission, and the need for firm capacity to balance supply and demand during operation. Such aspects are usually disregarded in global models such as GCAM. Another useful application of EMPIRE, beyond typical power sector studies, is using the model to estimate inputs for life cycle assessment studies. Independent estimation of utilization of different generation technologies neglects the fact that the actual production is a result of an economic dispatch, which strongly depends on the configuration of the system. Improving estimation of utilization of technologies is important for accurate assessment of environmental impacts.

Modeling results

From the overall results presented in the different papers some general insights about the future development of the European power sector can be drawn. Firstly, the most cost-efficient deployment strategy for intermittent renewables is to centralize investments where the production potential is high. Investments in wind and solar capacity should be accompanied by significant reinforcement of the transmission system as this will enable efficient sharing of generation resources. Even with significant deployment of wind generation, and transmission system expansion, carbon-capture and storage plays a pivotal role in decarbonizing European power. If transmission system development for some reason should end up to be low, less wind generation should be expected, and CCS becomes even more important. Without CCS, the carbon price needed to achieve the ambitious goals for emission reduction in Europe, will have to be higher than the price found in the European Commission's reference scenario 2013 report. Essentially, the cost of decarbonization will be higher. Without successful deployment of demonstration CCS projects, the technology will not be available as a tool for emission reduction. Therefore it is important to implement measures which can establish a secure investment environment for demonstration CCS.

Although there has been a record development in installed capacity of solar photovoltaic (PV) in Europe over the recent years,[2] the technology is not found to be a significant low-carbon option in most of the analyses done with EMPIRE.[3] This can be explained by the fact that renewable support policies are not represented in EMPIRE, and also, that the investment costs assumed for solar PV in EMPIRE are too high for the technology to become competitive. This suggests that investment cost reductions for solar PV is still needed for the technology to be competitive without support policies in place.

4.1 Further research

There are a number of different directions possible for research building on the work presented here. Naturally, new studies on various topics related to the European power sector, using the current version of EMPIRE, can be produced. Even though studies and analyses using existing

2. EurObserv'ER, `http://www.eurobserv-er.org/category/all-photovoltaic-barometers/`, reports an increase of 550 % for installed solar PV capacity in the European Union from the start of 2010 to the start of 2015. [Accessed March 2016]

3. In Brovold, Skar, and Fosso (2014) solar PV investments in EMPIRE were seen to increase significantly when using a water-value based handling of hydro power generation with reservoir. This is not consistent with other studies done with EMPIRE, and the result is therefore a bit unclear.

tools are certainly important, I would like to focus this section on a few modeling developments for EMPIRE, which I believe would be the most useful in terms of new research contributions.

One of the key weaknesses of the current version of EMPIRE is the transmission system representation. Transmission capacity investment costs are based on €/MW/km figures found in Joode et al. (2011), and distances between geographical mass points defined by visual inspection. This is a crude approximation, essentially reflecting the cost of building new (over-lay) grid corridors in straight lines across entire countries. In some scenarios, for instance with highly centralized renewable generation capacity expansions, this may be a valid strategy for transferring bulk power between countries throughout Europe. However, solutions where the grid reinforcements are done mostly for cross-border connections, relying on national grids to transfer power from border to border, are not considered. As discussed in Section 2.1.1, there are examples of more refined approaches to this issue in the literature. The current best practice in terms of transmission investment analysis of the European grid is the full linearized dc optimal power flow model with endogenous investments presented in Egerer, Gerbaulet, and Lorenz (2013). The draw-back of using such a detailed model is that the temporal horizon of the operational modeling must be significantly limited, and the investments evaluated using a myopic approach, for the optimization problem to stay tractable. A second-best approach is shown in Fürsch et al. (2013), where a capacity expansion model is run in conjunction with a detailed grid power flow model. The capacity expansion model decides optimal cross-boarder NTC expansion, while the power flow model is used to determine which lines have to be reinforced and cost estimates. The advantage of such a setup is far more accurate costs estimates than what is available in EMPIRE, however, a disadvantage is that an additional model is required. Within the current modeling framework of EMPIRE, a straightforward improvement would be to split larger countries such as Germany, France and Spain into several nodes as has been done by Schaber, Steinke, and Hamacher (2012). This would allow for some of the large national grids to be part of the analysis, and most likely make it easier to assess costs for reinforcing specific corridors as the distances between nodes would be reduced. As all of these modeling approaches already are incorporated in other models, improving transmission system modeling in this way may perhaps not qualify as further research. However, even if an already well-known approach is adopted, improving the transmission system representation in EMPIRE will likely entail a need for developing better algorithms for solving the model as it will become more challenging to solve. The joint effort of improving the modeling features of EMPIRE, while keeping the model computationally tractable, and improving algorithms for solving it, can certainly contribute to new and useful research results.

Although a technique meant to improve the handling of hydro power generation with reservoir is presented in Brovold, Skar, and Fosso (2014), it may still be useful to revisit this issue with an alternative approach. The procedure presented by Brovold, Skar, and Fosso (2014) involved using a specialized large-scale power market model to compute water-values. Linking of models in this way requires a great deal of care in order to harmonize system assumptions between them. Future development on this topic should focus on including seasonal storage handling directly in EMPIRE, circumventing the need for additional models. One option is to incorporate an auxiliary medium-term optimization problem in the operational modeling. In this problem, the amount of energy to save between seasons can be approximated based on a rudimentary seasonal dispatch model. Decision variables reflecting the stored energy can be linked to the short-term hourly dispatch seasons, and everything solved in a single optimization (just as investments and operational decisions are currently co-optimized).

As discussed in Section 2.1.2 EMPIRE assumes perfect foresight when it comes to strategic parameter input data such as fuel prices, demand projections, future policies, etc. The investment strategies computed by EMPIRE are therefore tailored for a specific set of input data, and may perform poorly in a future with a different outcome. A further application of the multi-horizon tree methodology developed by Kaut et al. (2014), by incorporating strategic uncertainty as well as operational uncertainty, would be a way to address this issue while keeping the resulting optimization problem to a solvable size. The value added would first of all be more robust investment strategies. Secondly, studies could address how strategic uncertainty affect timing and sizing of investments. This can be important for emerging technologies like CCS, which rely on capital intensive investments in demonstration projects prior to commercialization.

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Papers

Paper A

Skar, C., G. L. Doorman, and A. Tomasgard. 2014b. "The future European power system under a climate policy regime." In *EnergyCon 2014, IEEE International Energy Conference,* 337–344. doi:10.1109/ENERGYCON.2014.6850446.

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Paper B

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Paper C

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Implementing hydropower scheduling in a European expansion planning model

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Abstract

A method for implementing an enhanced hydropower planning formulation in a long-term expansion planning model is proposed. The methodological framework involves assigning hydropower generation a marginal cost through water values, enabling comparability with the marginal costs of competitive technologies. Added robustness and details in the representation of hydropower and its inherent storage capabilities allows for a more precise evaluation of the technology's impact on optimal investments for other power resources. The impact for intermittent renewable energy sources such as wind and solar power is especially interesting to analyze. Examination of effects from the richer formulation is carried out for an EU 20-20-20 like policy scenario. Optimization results for Europe in the period 2010 to 2060 show that the new framework leads to decreased utilization of hydropower due to its more precise valuation through water values, as well as lower inflow for run-of-the-river hydropower than previously. Therefore, additional investments are carried out for other energy sources that are deemed more economically beneficial. Notably, an earlier deployment of solar power is part of the revamped investment scheme.

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Keywords: Hydropower; emission reduction policy; GEP; generation planning; optimization

1. Introduction

The goal of generating enough energy to sustain the rapidly increasing global population, while simultaneously minimizing environmental impacts associated with energy extraction and consumption is a global pursuit of supreme importance. Models have been developed to analyze how this goal can be met at lowest possible cost. One

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of these is the EMPIRE[†] model, which is a European power investment model capable of incorporating various climate policy scenarios. Its framework is the starting point for the work presented in this paper, which consists of improving how hydropower is formulated in EMPIRE. One of the main objectives for doing so is to enable a more precise analysis of synergetic effects between installments of hydropower and intermittent renewables. The ongoing and future large-scale implementation of such variable generation introduces additional fluctuations in the power system and thereby new challenges in the continuous balancing of supply and demand [1]. Regulated hydropower can respond more or less immediately to fluctuations and can act as an ancillary service that regains balance in the power system [2]. This way, hydropower may support further investments in intermittent renewables.

Nomenclature

SYMBOL		DESCRIPTION	SYMBOL	DESCRIPTION
Sets and indices			**Parameters cont.**	
G	g	Generators	$F^{init}_{ns\omega}$	Initial reservoir fraction of full reservoir
H	h	Operational hours: H_s in a season, H_i in a year	$R^{init}_{ns\omega}$	Initial reservoir level [MWh]
I	i	Years	R^{max}_{n}, R^{min}_{n}	Max. and min. reservoir level [MWh]
L	l	Transmission lines	$R^{temp}_{ns\omega}$	Temporary reservoir level [MWh]
M_n	m	Reservoir segments	$U^{Reg,norm}_{ns\omega}$	Seasonal normalized inflow [MWh]
N	n	Nodes (one per country)	$U^{Reg,init}_{ns\omega}$	Seasonal inflow in 2010 (initial) [MWh]
S	s	Seasons	$U^{RoR,norm}_{ns\omega}$	Seasonal run-of-the-river inflow [MWh]
Ω	ω	Stochastic scenarios	S^{max}_{mn}	Maximum reservoir segment size [MWh]
Decision variables			$xd^{max}_{mns\omega}$	Actual reservoir segment size [MWh]
$xd_{mnsi\omega}$		Segmental discharge [MWh]	$WV_{mnsi\omega}$	Water value [$/MWh]
$r_{nsi\omega}$		End-of-season reservoir level [MWh]	α_h	Operational hour scale factor
$s_{nsi\omega}$		Spillage [MWh]	ϑ_s	Seasonal scale factor
p^{gen}_{gi}		Generation capacity [MW]	δ_i	Discount factor
x^{gen}_{gi}		Gen. capacity investment [MW]	ν_s	Number of hours in season
x^{tran}_{li}		Line capacity investment [MW]	p_ω	Scenario probability
$y^{gen}_{ghi\omega}$		Generation [MWh]	c^{gen}_{gi}	Generator investment cost [$/MW]
$y^{LL}_{nhi\omega}$		Load shedding [MWh]	c^{tran}_{li}	Transmission investment cost [$/MW]
Parameters			q^{gen}_{gi}	Generator short-run marginal cost [$/MWh]
N^{seg}		Number of segments in reservoir	q^{VoLL}_{ni}	Cost of using load shedding [$/MWh]

1.1. Related literature

There exist a vast number of optimization models used for investment planning and policy studies in Europe. Recent notable examples of linear programming models, where new generation and transmission investments are co-optimized with a system dispatch, are presented in [3] and [4]. The former model has since been adapted to detailed studies of long-term grid extensions in Europe, see [5], and a study of decarbonization of the European power sector, see [6]. In [7] a dedicated hydropower scheduling model is used to compute water values for seasonal

[†] **E**uropean **M**odel for **P**ower system **I**nvestment with (high shares of) **R**enewable **E**nergy

hydropower reservoirs, which are consequently used in a detailed DC load flow model of Northern Europe. This is similar to what has been done in this paper, although in this setting we focus on long-term system expansion.

1.2. Brief overview of the EMPIRE model

The purpose of the EMPIRE model is to provide a long-term plan for timing, size and location of investments in generation capacity and inter-country transmission capacity in Europe. This is done through cost minimization in the period 2010 to 2060, subject to various policy scenarios. EMPIRE is formulated as a linear, two-stage stochastic optimization model and has been implemented in Mosel Xpress [8]. The spatial resolution of EMPIRE is based on country-wise aggregation where each country represents a node *n* in the system. Investments can take place in 5-year leaps. Each year *i* is modeled as 10 non-consecutive seasons *s*, constituted by a number of operational hours *h* in which load balances are requested. Stochastic scenarios ω account for uncertainty related to some parameters such as load and generation from intermittent energy sources. Generation capacities, annual build limits and a number of other restrictions are included. For more information about the EMPIRE model, see [9]. In the next chapter, the strategy for improving the hydropower framework will be described.

2. Hydropower scheduling methodology

Regulated and run-of-the-river hydropower are modeled independently. In the original EMPIRE model, regulated hydropower availability comes at no cost, aside from low operation and maintenance costs. Thus, the model will tend to empty the reservoirs towards the end of each season, since the water is virtually free. This is a major simplification of real-world conditions, where the use of water values as marginal cost for hydropower generation is a widespread means of assigning monetary values to the available water resources. The water value can be defined as the future expected value of the stored marginal kWh of water, i.e. its alternative cost [10]. Therefore, it will generally be optimal to generate power from a unit of water whenever the water value is lower than the expected power price, or save the unit in the opposite case. This introduces the significance of saving water to other periods of the year, which is not present in the original EMPIRE model. Since seasons are modeled individually, the original formulation has no incentive to conserve water for later periods. The use of water values is one method of enabling this water-saving feature, and is the key concept of the improvement strategy we propose.

The methodology starts by dividing each reservoir into *M* segments of equal size, and each of these segments are given an associated water value. In the start of each season we set an initial reservoir level based on a fractional value of a full reservoir. Inflow to the reservoir is assumed to take place immediately in the beginning of a season, which can be justified by the short season durations in the model. As the reservoir level is reduced the water values increase, since the water becomes more valuable as the available amount decreases. When assuming that the lowest index number indicates the top-most reservoir segment, the inequality $WV_0 < WV_1 < \ldots < WV_{m-1} < WV_m$ must therefore hold for all segments $m \in M$.

2.1. Mathematical formulation

In this section we describe the mathematical framework for enhanced hydropower. The implementation of hydropower scheduling is done in two separate steps. The first step utilizes reservoir data to determine the available amount of energy in each reservoir segment, setting the bounds for segmental discharge. The second step includes restrictions for generation and reservoirs, and is given in the following. Reservoir discharge is connected with hydropower generation as

$$\sum_{h \in H_s} y^{gen}_{ghi\omega} = \sum_{m \in M_n} xd_{mnsi\omega}, \quad n \in N, g \in G^{HydReg}_n, s \in S, i \in I, \omega \in \Omega \qquad (1)$$

It is necessary to keep track of the reservoir level at the end of each season. The end-of-season reservoir level is equal to initial reservoir level plus inflow minus total segmental discharge and spillage. This is shown in Eq. (2), while minimum and maximum reservoir levels are shown in Eq. (3):

$$r_{nsi\omega} = R_{ns\omega}^{init} - \sum_{m \in M_n} xd_{mnsi\omega} + U_{ns\omega}^{Reg,norm} \cdot p_{gi}^{gen} - s_{nsi\omega}, \quad n \in N, g \in G_n^{HydReg}, s \in S, i \in I, \omega \in \Omega \tag{2}$$

$$R_n^{min} \leq r_{nsi\omega} \leq R_n^{max}, \quad n \in N, s \in S, i \in I, \omega \in \Omega \tag{3}$$

The multiplication of installed capacity in the inflow term of Eq. (2) is done because we assume that changes in capacity also influence the available amount of inflow. Segmental discharge bounds are represented as follows:

$$xd_{mnsi\omega} \leq xd_{mns\omega}^{max}, \quad m \in M_n, n \in N, s \in S, i \in I, \omega \in \Omega \tag{4}$$

For some nodes with small reservoirs and thereby a low degree of regulation, the water values of some segments may be identical. In these cases the discharge sequence has to be controlled through

$$xd_{m+1,nsi\omega} \leq xd_{mnsi\omega}, \quad m \in \left\{1, \ldots, N^{seg} - 1\right\}, n \in N, s \in S, i \in I, \omega \in \Omega \tag{5}$$

This constraint states that discharge from segment *m+1* cannot start unless discharge from segment *m* has been initiated. To keep reservoirs sustainable, it is assumed that yearly generation cannot exceed yearly inflow:

$$\sum_{h \in H_i} \alpha_h \cdot y_{ghi\omega}^{gen} \leq \sum_{s \in S} \vartheta_s \cdot U_{ns\omega}^{Reg,norm} \cdot p_{gi}^{gen}, \quad n \in N, g \in G_n^{HydReg}, i \in I, \omega \in \Omega \tag{6}$$

Run-of-the-river (RoR) hydropower can be modeled in a simpler manner. Inflow is used to bound the hourly generation as a continuous, no-cost power availability. Eq. (7) describes an hourly generation limit based on the average hourly inflow value for all hours in season *s*:

$$y_{ghi\omega}^{gen} \leq \frac{U_{ns\omega}^{RoR,norm} \cdot p_{gi}^{gen}}{\nu_s}, \quad n \in N, g \in G_n^{HydRoR}, h \in H, s \in S, i \in I, \omega \in \Omega \tag{7}$$

The objective function seeks to minimize the net present value of investment costs and expected operational costs over all years $i \in I$. With the hydropower scheduling modeled as above, it can now be formulated as

$$\min_{\mathbf{x},\mathbf{y}} z = \sum_{i \in I} \delta_i \times \left\{ \sum_{g \in G} c_{gi}^{\text{gen}} x_{gi}^{\text{gen}} + \sum_{l \in L} c_{li}^{\text{tran}} x_{li}^{\text{tran}} + \sum_{\omega \in \Omega} p_\omega \left(\begin{array}{l} \sum_{h \in H} \alpha_h \times \sum_{n \in N} \left(\sum_{g \in G_n} \left[q_{gi}^{\text{gen}} y_{ghi\omega}^{\text{gen}} \right] + q_{ni}^{\text{VoLL}} y_{nhi\omega}^{\text{LL}} \right) \\ + \sum_{s \in S} \vartheta_s \times \sum_{n \in N} \sum_{m \in M_n} xd_{mnsi\omega} WV_{mnsi\omega} \end{array} \right) \right\} \tag{8}$$

where the cost of utilizing regulated hydropower is represented by the last term: discharge from segment *m* multiplied by its water value for node *n*, season *s*, year *i* and stochastic scenario ω. The other terms include costs for generation and line transmission investments, power generation and lost load. Uncertainty for investment decisions is not considered because all parameters related to this stage are given deterministically in the EMPIRE model.

2.2. Data sets

Water values, maximum reservoir levels and regulated and run-of-the-river inflow has been collected from SINTEF Energy Research in Trondheim, Norway. In order to account for variations throughout the year, seasons have been divided into two categories, summer and winter. Values for initial reservoir levels are assumed higher in summer than winter. For the base scenario, 80 and 60 per cent are assumed to be initial levels for summer and winter seasons, respectively. The other scenarios use ranges from 70 to 90 per cent for summer and 50 to 70 per cent for winter. Initial reservoir levels for Norway and Sweden, the two countries with the largest reservoirs in the system, have been given more accurate data [11]. Minimum reservoir level is assumed to be 5 per cent of a full reservoir.

Due to difficulties related to computation of water values, it is noted that presented results are affected by inconsistent quality of these parameters. The EMPS model, see [10], was used to produce water values; however, the quality of the data set is modest for the years after 2010. As an approximation, we have therefore introduced generation restrictions for regulated hydropower, limiting generation from 2015 to 2060 to a 20 per cent deviation band from the generation in 2010 on a seasonal country-wise level. While large expansions of regulated hydropower in Europe is not expected in the coming decades [12], incorporating such limits is unquestionably a simplification. As such, results do not reflect our final investment recommendations, but can rather be seen as projection guidelines.

Global Change Assessment Model, see [13], provides expected generation shares for various technologies throughout the planning period, given policy scenarios. We utilize these shares in the model, though with two relaxations: Hydro-, wind and solar power are entirely excepted from the GCAM matching constraints, and a deviation allowance of 40 per cent from the GCAM values are embraced for the remaining technologies. Adding these relaxations allows us to identify effects of the new hydropower formulation more clearly, while at the same time preserving some of the added stability by incorporating GCAM matching.

3. Optimization results and analysis

Optimization results are presented for the Global 20-20-20 policy scenario, which is an extension of the EU 20-20-20 scenario to a global scope [14]. The results show optimal values for Europe needed to comply with global targets. All original parameters in EMPIRE unrelated to hydropower are kept intact. It is evident that within the Global 20-20-20 policy regime, the framework favors wind to an extensive degree. As seen in Figure 1 the policy scenario involves large-scale expansions of renewables which take place early in the planning period. Fossil technologies are present in the entirety of the temporal scope, although with significantly lower amounts towards the end of the period, as a result of the increased penetration of renewables.

Differences between the original and the enhanced hydro version of EMPIRE, see Figure 2, show a significant increase in solar capacity for the final model, with a percentage-wise difference peaking in 2040 at 45 per cent. However, from 2050 both models find it optimal to reach maximum capacity of wind and solar power.

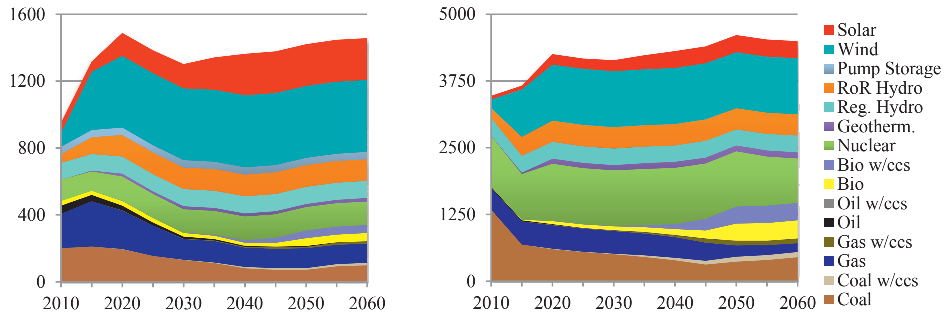

Figure 1: Generation capacity in GW (left) and generation mix in TWh/year (right) aggregated for the European power system.

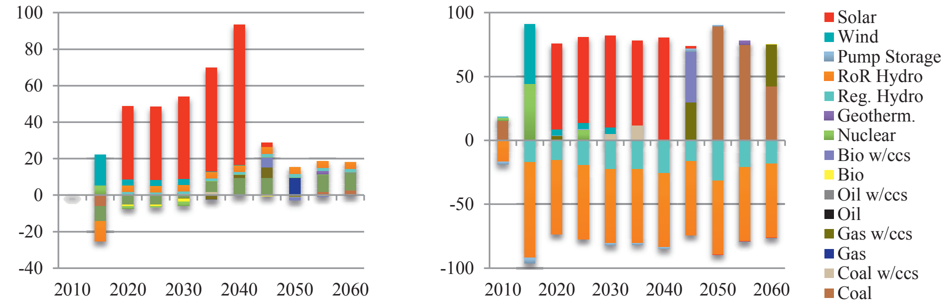

Figure 2: Generation capacity differences in GW (left) and generation mix differences in TWh/year (right) between the final and original models.

The combination of these findings suggests that the use of water values forces EMPIRE to invest in more capacity at an earlier stage, thereby increasing total costs. This can be explained through two effects: Regulated hydropower generation decreases due to more precise cost information through water values, and run-of-the-river hydropower generation is reduced because of a lower amount of available inflow. Consequently, hydropower is found to be overvalued in the original model.

While the combined hydropower generation is reduced, cheaper sources are selected as generation providers to take its place. In the first part of the planning period this is carried out by larger investments in solar power, mainly happening in Germany, Italy and Greece. The increased capacity availability is also reflected in the generation mix, with solar generation at a consistently higher level in the final model for the years 2020 to 2040. Indeed, in 2030 solar generation is 54 per cent higher than in the original model. For the last years, after solar has reached its system-wide maximum installed capacity, a higher utilization of coal serves as substitution supplier.

4. Conclusion

By implementing an enhanced hydropower formulation we have increased the level of detail for this energy source in the EMPIRE expansion planning framework. Results show that the original hydropower availability is too unconstrained, thereby causing an overvaluation of this technology. The revamped cost representation by means of water values leads to a lower utilization of hydropower relative to the original model. An earlier deployment of solar power is carried out to replace the lower generation. Total costs in the system are therefore increased. For both models, extensive investments in intermittent renewables are taking place, amounting to 47 per cent of the total capacity in 2060.

It is noted that the results presented are affected by inconsistent quality of the water values data set. The usefulness of the implementation is nonetheless valuable because of a more comprehensive and accurate representation of hydropower in this investment environment than previously. In further work, an in-depth study of water values parameters would be interesting to conduct.

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Paper D

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A multi-horizon stochastic programming model for the European power system

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Abstract

This paper presents the stochastic power system investment model EMPIRE. Formulated as a multi-horizon stochastic program EMPIRE incorporates long-term and short-term system dynamics, while optimizing investments under operational uncertainty. By decoupling the optimization of system operation at each investment period from future investment and operation periods, a computationally tractable optimization problem is produced. The use of EMPIRE is illustrated in a decarbonization study of the European power system for two cases, one with transmission infrastructure investments, and one without. A combination of onshore wind and thermal generation with carbon capture and storage (CCS) is shown to provide significant CO_2 emission reductions from 2010 to 2050, 85 % in the transmission expansion case and 82 % in the no expansion case.

Keywords: Stochastic programming, Energy system planning, Investment analysis, OR in energy

1. Introduction

As a response to the challenge to mitigate climate change the European Commission (EC) has supported a long-term commitment to reduce domestic greenhouse gas emissions in the European Union by 80–95 %, relative to 1990 levels (EC, 2009). In its 2011 "Energy Roadmap 2050" the EC shows that reaching this target will entail an almost complete decarbonization of the power sector (EC, 2011). This necessitates a large-scale deployment of renewable electricity production, in particular wind and solar power. However, owing to the intermittent and non-controllable nature of wind and solar generation, an increased share of these technologies in the generation mix imposes challenges in terms of balancing supply and demand. These aspects introduce short-term uncertainty

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which is important to consider when planning investments of generation technologies, transmission system and energy storage equipment throughout the system.

In this paper we present a stochastic programming model, EMPIRE (European Model for Power system Investment with Renewable Energy), developed to handle the challenges related to intermittent energy production and stochastic energy demand in a long-term investment model. To avoid the curse of dimensionality when modeling short-term uncertainty in a long-term model, we use the multi-horizon approach presented by Kaut et al. (2014). The main contribution of this model is that it simultaneously handles short-term dynamics, short-term uncertainty as well as long-term dynamics. We are not aware of other long-term spatial power sector models that do so, and we think these properties are critical when modeling the need for storage and other technologies, as a consequence of the short-term stochastic parameters related to renewable production and electricity demand. The model is demonstrated through a full-scale long-term analysis of cost-efficient decarbonization of the European power system.

First we review relevant power sector models that have been used for similar studies. In particular, we focus on how they handle short-term uncertainty and short-term dynamics when modeling system operation, and long term-dynamics related to investment decisions.

DIMENSION is an optimization based dynamic investment model for the European power system, developed at the Institute of Energy Economics University of Cologne (Richter, 2011). Jägemann et al. (2013) use the DIMENSION model for an extensive analysis of the European electric power sector, establishing the cost of decarbonization in 36 cases with a wide variety of policy regulations and assumptions regarding technology availability and economic conditions. Another optimization based investment model, the LIMES-EU$^+$, is used by Haller et al. (2012) to study decarbonization of the European power sector without the use carbon capture and storage (CCS) and nuclear power. There are similarities and differences between EMPIRE and these models. The DIMENSION model and the LIMES-EU$^+$ model are dynamic models, co-optimizing investment and operation over a long time horizon. However, both these models are deterministic while EMPIRE includes short-term uncertainty.

A dynamic, multi-stage stochastic version of the DIMENSION model is presented in Fürsch et al. (2013), where investments in generation capacity are done under uncertainty about renewable energy deployments. This is an example of incorporation of long-term uncertainty, which is different from the operational uncertainty considered in EMPIRE. Operational uncertainty is included in another version the DIMENSION model published in Nagl et al. (2013). In this version investments are done facing uncertainty in solar and wind production. Although this is similar to the approach used in EMPIRE when it comes to modeling uncertainty, the model is static, using a single investment period, and can therefore not be applied to address transitional development of the European system. EMPIRE, on the other hand, includes long-term dynamics by incorporating multiple investment periods.

There are also investment models for the European power system that consider how the short-term uncertainty affects operational decisions. In the E2M2 model, see Swider and Weber (2007), system operation is modeled as a multi-stage stochastic program, with uncertainty in intermittent power production represented using a recombining tree formulation. Investments are optimized in myopic single steps, and several periods are considered sequentially. E2M2 is used by Spiecker and Weber (2014) to analyze five policy story lines for emission reduction in Europe, with a focus on cost and technology mix development. Jaehnert et al. (2013) present a capacity expansion model based on the power market simulator EMPS, which is extended to incorporate endogenous investment decisions. EMPS is a stochastic dynamic programming model originally designed for power market analysis of hydro- dominated systems, and is used extensively for management of reservoirs for hydroelectric generation under uncertain inflow and market conditions (Wolfgang et al., 2009). Similarly to the E2M2 model, investments in the extended EMPS model are myopic for single steps. There are two important distinctions between EMPIRE and these two models. The E2M2 and EMPS models have sophisticated operational modeling, but investments are myopic. In EMPIRE all investment periods are included in a single optimization, but the details in the operational modeling is reduced for the model to remain tractable. Short-term uncertainty is considered, but only when investments are made. Operational decisions are made under (short-term) perfect foresight.

Seljom and Tomasgard (2015) discuss a methodology for including short-term uncertainty in the energy system investment framework TIMES. Similarly to EMPIRE short-term and long-term dynamics are considered. The resulting model is presented as a two-stage stochastic program with investment decisions as first stage variables and operational decisions as second stage variables. Essentially this approach is equivalent to the multi-horizon tree formulation used in EMPIRE, as here-and-now short-term decisions are decoupled from future decisions.

Our work extends the body of modeling work already done on the topic of decarbonization of European power. The methodological contribution in this paper is the description of the capacity expansion model EMPIRE which includes

1. long-term dynamics: multiple investment periods
2. short-term dynamics: multiple sequential operational decision periods and market clearing
3. short-term uncertainty: multiple scenarios for input data describing operating conditions (wind, solar and load profiles, hydro power production limits, etc.)

While the full mathematical description of EMPIRE has not been published, previous versions of the model have been used to assess implications of global climate mitigation strategies for the European power system, see Skar et al. (2014), and for several studies of CCS deployment in Europe organized by Zero Emissions Platform (ZEP, 2013, 2014, 2015).

The structure of the paper is as follows: Section 2 presents EMPIRE, its design, mathematical formulation and a stochastic scenario generation routine. Section 3 presents a case study of European power decarbonization using the EU 2013 reference case data EC (2014).[1] Following the analysis, the final section presents the conclusions of the study. Lastly, a list of symbols used in the mathematical description of EMPIRE, and a discussion on input data sources and preprocessing are included in appendices at the end.

[1] In order to avoid confusion over the use of the word *scenario* (in this paper used for stochastic scenarios) we label the input data from EC (2014) as the *EU reference case 2013* rather than the actual name used by the European Commission, namely EU (energy, transport and GHG emissions trends to 2050) reference scenario 2013.

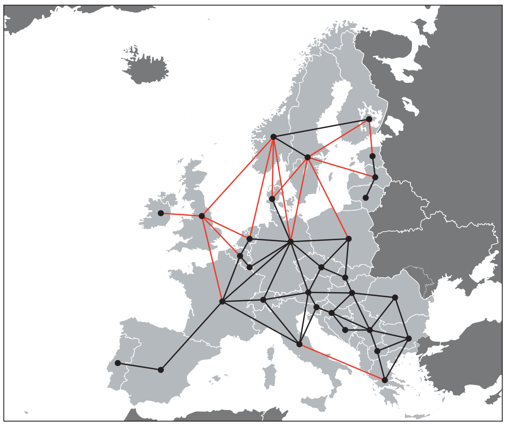


Figure 1: Spatial detail of the EMPIRE model. The coverage include all the nationalities represented in the ENTSO-E (as of 2010), except Cyprus, Iceland and Montenegro. This coincide with the EU-28 (less Cyprus and Montenegro) plus Bosnia Herzegovina, Norway, Serbia and Switzerland. As the expansion cost of high voltage (HV) cables are higher than for HV lines, these are identified using a red color in this figure.

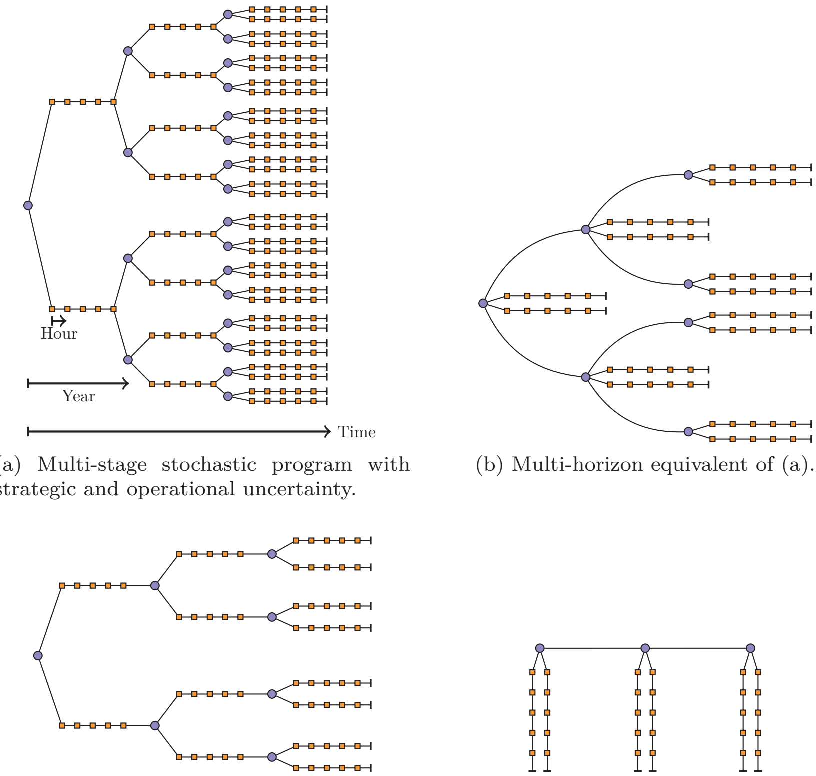
2. Approach

The European Model for Power System Investment with (high shares of) Renewable Energy (EMPIRE) is a capacity expansion model designed to assess optimal capacity investments and system operation over medium to long-term planning horizons, typically ranging 40–50 years. A total of 31 European countries are included in the model, connected through 55 interconnectors, as depicted in Figure 1. Following the tradition of recently developed models with similar scope, a central planner perspective is used, minimizing a system costs objective while serving a price inelastic demand (see Jägemann et al. (2013); Nagl et al. (2013); Spiecker and Weber (2014); Haller et al. (2012)). This is equivalent to an economic social surplus maximization, a commonly used model of perfectly competitive markets, with consumer decisions fixed ex ante. These types of models are often referred to as power market models, and are frequently in use for studying policy and regulation in the liberalized European power sector.

2.1. EMPIRE modeling structure

2.1.1. Multi-horizon tree formulation

The effect of short-term uncertainty about the system operating conditions on investment decision is captured by formulating EMPIRE as a stochastic programming model (Birge and Louveaux, 2011). Although, owing to its dynamic formulation, EMPIRE could have been cast as a standard multi-stage stochastic program, an alternative, approximate, formulation is applied. The methodology used is based on the principles of multi-horizon stochastic programming, as presented by Kaut et al. (2014). This is a framework for stochastic models exhibiting two time-scales for decisions and uncertainty, referred to as respectively long-term (strategic) and short-term (operational). As a precondition the strategic and operational uncertainty have to be represented by independent stochastic processes. The operational decisions are associated with a particular



(a) Multi-stage stochastic program with strategic and operational uncertainty.

(b) Multi-horizon equivalent of (a).

(c) Multi-stage stochastic program without strategic uncertainty.

(d) Multi-horizon equivalent of (c).

Figure 2: Examples of multi-scale multi-stage stochastic trees and their multi-horizon counterparts. Typical long-term and short-term time scales are shown in (a).

strategic stage, and the strategic decisions are made subject to operational uncertainty. However, it is assumed that current operational decisions, and the information learned from observing realized operational uncertainty, do not affect future strategic or operational decisions. Following this logic, it is possible to isolate current operational decisions from future decisions. Each strategic node will then have embedded operational nodes (which may incorporate further uncertainty, making it a sub-tree), however, there are no branches connecting operational nodes to future strategic nodes. This greatly reduces the total size of the tree. Figure 2 shows examples of full multi-stage stochastic programming problems and their reduced multi-horizon representation. Following the notation in Kaut et al. (2014) we let circles represent investment (strategic) decision stages (●) while squares represent operational decisions stages (■). Termination of a branch, in the sense that no future stages are directly linked to a given node is indicated by a line ($\perp$).

Stochastic energy system investment models naturally lend themselves to this classification, as both long-term investment decisions and short-term operational decisions are co-optimized. For power system models, typical strategic uncertainty may include long-term development in fuel prices and energy demand, policy and regulation, investment

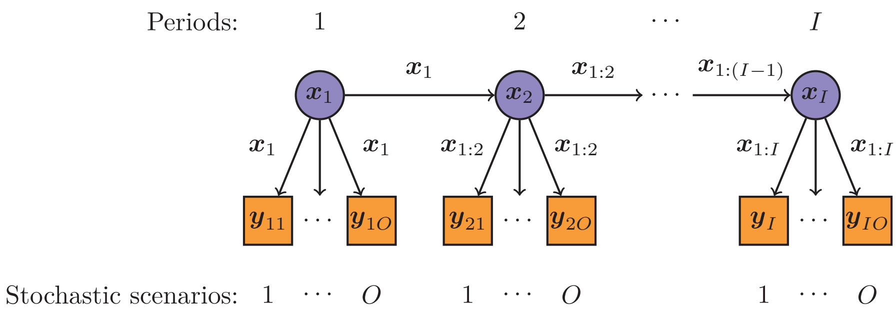


Figure 3: Temporal and stochastic scenario setup in EMPIRE. Circles indicate investment decision stages and squares indicate operational stages. Periods are indexed by the set $\mathcal{I}$ and the stochastic scenarios are collected in a finite sample space Ω.

costs and technology learning. Operational uncertainty, relates to the more short-term system dynamics: demand fluctuations, renewable energy production, short-term fuel price variability.

In the formulation of EMPIRE we have assumed perfect foresight in terms of the strategic data. The operational uncertainty is reflected in the load profiles, wind and solar generation profiles, and seasonal availability of water stored in reservoir for hydroelectric production. To simplify the exposition the same sample space $\Omega = \{1, \ldots, O\}$ is used for operational scenarios in every investment period, however, it should be noted that this is not a restriction of the multi-horizon tree formulation. The structure of the decision making process is shown in Figure 3. The vectors $\boldsymbol{x}_i$ are collection of strategic (investment) decisions in period $i \in \mathcal{I} = \{1, \ldots, I\}$, and $\boldsymbol{x}_{i:j}$ denotes the collection of vectors $\boldsymbol{x}_i, \boldsymbol{x}_{i+1}, \ldots, \boldsymbol{x}_j$, $i, j \in \mathcal{I}$. In the operational stages, $\boldsymbol{y}_{i\omega}$ is the collection of all the operational decisions (such as generation, line flows, storage handling etc.) in period $i \in \mathcal{I}$ and stochastic scenario $\omega \in \Omega$. For each period a strategic decision is made, subject uncertainty about which operational scenario $\omega \in \Omega$ will be realized.

The prefect foresight assumption used for long-term data leads to investment decisions tailored to fit a particular future in terms of fuel prices, carbon prices, demand growth, technological development, etc. However, the investments will account for the fact that operational conditions are difficult to predict at the time of the investment. In particular, the resulting investments will not be optimized for a single set of profiles for load and intermittent renewable production, but they will be optimized across several possible outcomes.

2.1.2. Temporal aggregation

In order to reduce the problem size, and computational effort of solving the optimization problem, two types of temporal aggregation schemes have been applied. As the main interest is the long-term expansion of the system, some dynamic granularity is sacrificed by considering five year time blocks rather than annual steps for the investment periods $i \in \mathcal{I}$. Capacity investments are assumed to be available starting from the same time period as the decision is made, and payments are done upfront.

A second step of the problem size reduction is used in the computation of annual

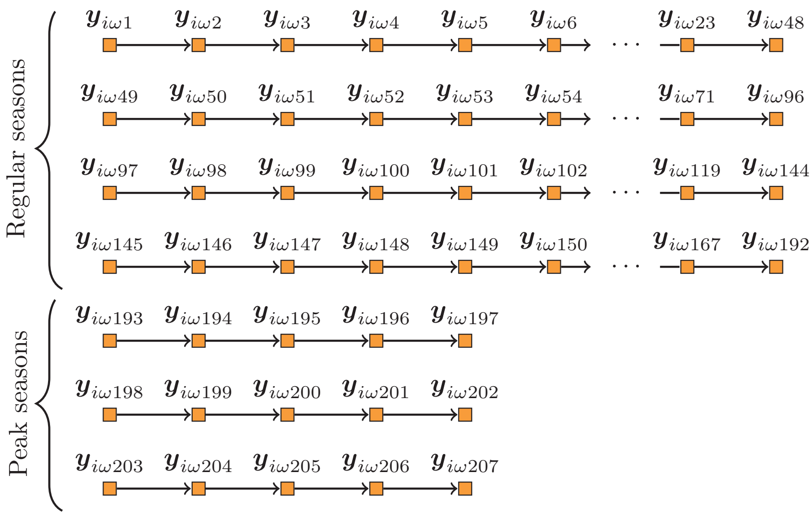


Figure 4: Illustration of the annual operation setup in EMPIRE. In this example there are four regular seasons, each with 48 consecutive hours, and three extreme load seasons, each with five consecutive hours.

operational costs. Rather than computing the system dispatch over a full year of 8760 hours we work with a reduced set of operational hours $\mathcal{H}$. The set $\mathcal{H}$ is subdivided into seasons, indexed by a set $\mathcal{S}$. EMPIRE applies a distinction between two types of seasons, regular seasons and extreme load seasons, with different numbers of operational hours modeled. The extreme load seasons are assumed to cover just a small fraction of the year, but they are useful for determining the need to install back-up capacity. By including these seasons in the operational modeling, the contribution of intermittent renewables in the electricity supply during such periods can be evaluated for a number of different scenarios. An approach similar to this, albeit in a deterministic setting, was used by Haller et al. (2012), where the normal operation was modeled using four seasons, each with three days divided into four time slices of six hours. For representing constrained supply situations they included an additional time slice, assuming high load and low renewable generation.

Figure 4 illustrates the temporal connection between operational decision vectors $\{\boldsymbol{y}_{i\omega h}\}_{h\in\mathcal{H}}$ in a given period $i \in \mathcal{I}$ and stochastic scenario $\omega \in \Omega$ (the full collection correponds to $\boldsymbol{y}_{i\omega}$ in Figure 3). As a matter of convenience the elements in $\mathcal{H}$ are labeled consecutively, $\mathcal{H} = \{1, \ldots, H\}$, although two consecutive hours in $\mathcal{H}$ are only consecutive in the modeling if they belong to the same set $\mathcal{H}_s$, for a season $s \in \mathcal{S}$.

A routine for scenario generation used to structure the operational data, as shown in Figure 4, has been created specifically for EMPIRE. This is documented in Section 2.3.

2.2. Mathematical formulation

In the following a complete description of the mathematical formulation of EMPIRE is provided, focusing on how the equations describe the investment and operation decision process. The actual implementation of EMPIRE is done using the Xpress-Mosel environment of the FICO® Xpress Optimization Suite (Heipcke, 2012; FICO®, 2015).

2.2.1. Objective function

The objective in EMPIRE is to minimize the sum of investment and (expected) operational costs for the system as whole, over all time periods in $\mathcal{I}$, discounted at rate r. Capacity investments are possible for generators $g \in \mathcal{G}$, denoted by decision variable x^{gen}_{gi}, and interconnectors $l \in \mathcal{L}$, denoted by x^{tran}_{li}. Storages, $b \in \mathcal{B}$, are modeled by a power (charge/discharge) capacity and an energy storage capacity, for which the investment decision variables are denoted by x^{storPW}_{bi} and x^{storEN}_{bi}, respectively. The investment costs are assumed linear as a function of the investment size for all assets, and the cost coefficients are given by c^{gen}_{gi} for generators, and by c^{tran}_{li} for interconnectors. For storages the power and energy investment costs are denoted by c^{storPW}_{bi} and c^{storEN}_{bi}. The investment cost parameters include capital costs, and fixed operation and maintenance costs, paid over the lifetime of an asset. For assets with life times expiring beyond the analysis horizon given by $\mathcal{I}$, the investment cost parameters are adjusted to account for salvage value.

In the expression for system operational costs, the model assumes linear production cost profiles for all generators. For a dispatch hour $h \in \mathcal{H}$, in period $i \in \mathcal{I}$ and stochastic scenario $\omega \in \Omega$, the decision variables describing generator production output are denoted by $y^{\text{gen}}_{ghi\omega}$, for $g \in \mathcal{G}$. The production cost coefficients, q^{gen}_{gi}, reflect all variable costs: fuel costs, carbon emission costs, operation and maintenance costs, and carbon capture and storage costs. These interpreted as short-run marginal costs (SRMC) due to the linear formulation. At every node $n \in \mathcal{N}$ the model has the ability to reduce load if it cannot be met by other means such as generation, import or storage discharge. The cost of load shedding is given by the product of the load shedding amount, $y^{\text{ll}}_{nhi\omega}$, and the value of lost load (voll), denoted by q^{ll}_{ni}.

The objective function is formulated as

$$\begin{aligned}
\min_{\boldsymbol{x},\{\boldsymbol{y}_\omega\}_{\omega\in\Omega}} z = &\sum_{i\in\mathcal{I}}(1+r)^{-5(i-1)}\times \\
&\Bigg\{\underbrace{\sum_{g\in\mathcal{G}} c^{\text{gen}}_{gi}x^{\text{gen}}_{gi} + \sum_{l\in\mathcal{L}} c^{\text{tran}}_{li}x^{\text{tran}}_{li} + \sum_{b\in\mathcal{B}}\left(c^{\text{storPW}}_{bi}x^{\text{storPW}}_{bi} + c^{\text{storEN}}_{bi}x^{\text{storEN}}_{bi}\right)}_{\text{Investment cost for generation, transmission and storage capacity, period } i} \\
&+ \vartheta\sum_{\omega\in\Omega}\pi_\omega\sum_{s\in\mathcal{S}}\alpha_s\sum_{h\in\mathcal{H}_s}\underbrace{\sum_{n\in\mathcal{N}}\left[\sum_{g\in\mathcal{G}_n}\left(q^{\text{gen}}_{gi}y^{\text{gen}}_{ghi\omega}\right) + q^{\text{ll}}_{ni}y^{\text{ll}}_{nhi\omega}\right]}_{\substack{\text{System operation cost (all nodes } n\text{),}\\ \text{generation + value of lost load,}\\ \text{period } i\text{, scenario } \omega\text{, season } s\text{, hour } h}}\Bigg\}. \qquad (1)
\end{aligned}$$

The collection $\{\pi_\omega\}_{\omega\in\Omega}$ comprises discrete probabilities on the finite sample space Ω, which makes the sum of operational costs over all $\omega \in \Omega$ scaled with π_ω an expected value.

In order to account for problem size reduction, as discussed in the previous section, we use scaling factors to ensure that investment and operational costs have the same temporal resolution. The factor ϑ is a five year inverse capital recovery factor,[2] scaling

[2] $\vartheta = \sum_{j=0}^{4}(1+r)^{-j} = \frac{(1+r)^5-1}{r(1+r)^4}$

annual values to a five year value, a necessity due to the use of five year block periods $i \in \mathcal{I}$. The scaling factors α_s, for season $s \in \mathcal{S}$, account the contribution parameters and variables in different seasons have to an annual figure. As an example, suppose that we define the total generation in season $s \in \mathcal{S}$, period $i \in \mathcal{I}$ and stochastic scenario $\omega \in \Omega$ as $Y^{\text{gen}}_{si\omega} = \sum_{h \in \mathcal{H}_s} \sum_{g \in \mathcal{G}} y^{\text{gen}}_{ghi\omega}$. Then $Y^{\text{gen}}_{i\omega} = \sum_{s \in \mathcal{S}} \alpha_s Y^{\text{gen}}_{si\omega}$ is the total annual generation in period i, scenario ω. The expected annual generation in period i is $Y^{\text{gen}}_{i} = \sum_{\omega \in \Omega} \pi_\omega Y^{\text{gen}}_{i\omega}$.

2.2.2. Dispatch model

The system operation is governed by a number of energy balance constraints, one for every node and every dispatch hour considered, and a number of technical constraints for the generators and interconnector links between nodes. The collection of all of the following constrains for a period $i \in \mathcal{I}$ and stochastic scenario $\omega \in \Omega$ define the annual dispatch of the system.

For every hour, $h \in \mathcal{H}$, the sum of net local generation and net import is required to balance the load at every node, $n \in \mathcal{N}$, denoted by the parameter $\xi^{\text{load}}_{nhi\omega}$. We let $y^{\text{flow}}_{ahi\omega}$ be the unidirectional flow on an arc connecting node n to a neighboring node in the network (see Figure 1). For each node the sets $\mathcal{A}^{\text{in}}_n$ and $\mathcal{A}^{\text{out}}_n$ contains the arcs going into, or out from, node n, respectively. Transmission losses are accounted for at the importing node, by down-scaling the flows for arcs $a \in \mathcal{A}^{\text{in}}_n$ by efficiency parameters η^{tran}_a, where $\eta^{\text{tran}}_a \in (0,1)$. The decision variables $y^{\text{chrg}}_{bhi\omega}$ and $y^{\text{dischrg}}_{bhi\omega}$ denote storage charging and discharging variables, and η^{dischrg}_b the discharge efficiency ($\eta^{\text{dischrg}}_b \in (0,1)$). The sets $\mathcal{G}_n$ and $\mathcal{B}_n$ contain the generators and energy storages, respectively, which are located at node n. The single hour node load balance, or dispatch, constraint is formulated as

$$\underbrace{\sum_{g \in \mathcal{G}_n} y^{\text{gen}}_{ghi\omega}}_{\text{Generation}} + \underbrace{\sum_{b \in \mathcal{B}_n} \eta^{\text{dischrg}}_b y^{\text{dischrg}}_{bhi\omega} - y^{\text{chrg}}_{bhi\omega}}_{\text{Storage handeling}} + \underbrace{\sum_{a \in \mathcal{A}^{\text{in}}_n} \eta^{\text{tran}}_a y^{\text{flow}}_{ahi\omega} - \sum_{a \in \mathcal{A}^{\text{out}}_n} y^{\text{flow}}_{ahi\omega}}_{\text{Net import}} = \xi^{\text{load}}_{nhi\omega} - y^{\text{ll}}_{nhi\omega},$$
$$n \in \mathcal{N}, h \in \mathcal{H}, i \in \mathcal{I}, \omega \in \Omega.$$

The nodal load is by this design price insensitive, apart from in highly constrained supply situations when load can be shed at the cost of value of lost load. The shadow prices of the node load balance constraints are reported as power prices. Uncertainty in the load profiles is introduced by using unique input data for every $\omega \in \Omega$.

Every generator, interconnector and storage (power and energy) have rated maximum installed capacities, v^{**}_{*i}, which for every period $i \in \mathcal{I}$ are given by the initial capacity still in operation, $\overline{x}^{**}_{*i}$, and cumulative investments which have not expired their lifetime, i^{life}_*.[3] Asterisks $**$ are used to indicate type of capacity (generator, line, storage power or storage energy) and $*$ indicate the element in the set of all objects of the given type (e.g. $g \in \mathcal{G}$ for generators), allowing for a generic definition of capacity. This is given as

$$v^{**}_{*i} = \overline{x}^{**}_{*i} + \sum_{j=i'}^{i} x^{**}_{*j}, \quad i' = \max\{1, i - \lfloor i^{\text{life}}_* / 5 \rfloor\}, i \in \mathcal{I}.$$

[3]The investment life time parameters are given in years, while the periods $i \in \mathcal{I}$ represents five year time blocks. When determining if an asset is active in period i the life time parameters must be divided by 5. The $\lfloor \cdot \rfloor$ notation is used for the floor operator.

Vintage and new capacities are aggregated as we consider each generator, interconnector and storage to represent the installed capacity for a given period $i \in \mathcal{I}$. For thermal and hydro generators, $g \in \mathcal{G}^{\text{Thermal}} \cup G^{\text{Hydro}}$, v^{gen}_{gi} is the total installed capacity of a technology at a given node. As an example, nuclear power in France is considered one generator. Pooling generation resources this way reduces the number of decision variables in the dispatch problems, however, the trade-off is that the model cannot keep track of the age distribution of a technology when computing the optimal dispatch. As a result, if a technology is improved from one investment period to the next, the improvement is applied to the entire power plant fleet of that technology. Wind and solar generators are not aggregated by technology in the same way, but represents locations within a country with different production resource potentials.

Production from each generator for a dispatch hour is limited by the available installed capacity. We use availability parameters, $\xi^{\text{gen}}_{ghi\omega}$, where $\xi^{\text{gen}}_{ghi\omega} \in (0,1)$, to derate the installed capacity for generator $g \in \mathcal{G}$ in hour $h \in \mathcal{H}$. The maximum production constraint is then

$$y^{\text{gen}}_{ghi\omega} \leq \xi^{\text{gen}}_{ghi\omega} v^{\text{gen}}_{gi}, \quad g \in \mathcal{G}, h \in \mathcal{H}, i \in \mathcal{I}, \omega \in \Omega,$$

For intermittent production, such as wind power and solar power, the availability parameters are stochastic and represented by scenario dependent normalized production profiles. These profiles have an hourly scale, and the data used is generated by the routine described in Section 2.3. As for the load parameters, the intermittent production profiles are unique for each stochastic scenario $\omega \in \Omega$, reflecting the operational uncertainty experienced at the time of investment. For thermal generators the availability parameters are constant across all hours $h \in \mathcal{H}$, and are based on average capacity factors for the given technologies.

Ramp up of production for thermal generators, $g \in \mathcal{G}^{\text{Thermal}}$, is assumed to be limited to a certain share of the installed capacity, given by the parameter γ^{gen}_{g}, where $\gamma^{\text{gen}}_{g} \in (0,1)$. The ramping constraints are formulated as

$$y^{\text{gen}}_{ghi\omega} - y^{\text{gen}}_{g(h-1)i\omega} \leq \gamma^{\text{gen}}_{g} v^{\text{gen}}_{gi}, \quad g \in \mathcal{G}^{\text{Thermal}}, s \in \mathcal{S}, h \in \mathcal{H}^{-}_{s}, i \in \mathcal{I}, \omega \in \Omega.$$

The decision variables $w^{\text{stor}}_{bhi\omega}$ keep track of the energy level for storage $b \in \mathcal{B}$. At every hour (except the first in a season), the storage end-level is set as the difference between the energy level in the previous hour minus the net discharge. The storage energy-balance constraint is given as

$$w^{\text{stor}}_{b(h-1)i\omega} + \eta^{\text{chrg}}_{b} y^{\text{chrg}}_{bhi\omega} - y^{\text{dischrg}}_{bhi\omega} = w^{\text{stor}}_{bhi\omega}, \quad b \in \mathcal{B}, s \in \mathcal{S}, h \in \mathcal{H}^{-}_{s}, i \in \mathcal{I}, \omega \in \Omega.$$

Losses are attributed both to the charging and discharging of the energy storage, and the round-trip efficiency is given as $\eta^{\text{roundtrip}}_{b} = \eta^{\text{chrg}}_{b} \eta^{\text{dischrg}}_{b}$. The stored energy and charging/discharging are limited by the energy and power installed capacities, given by

$$w^{\text{stor}}_{bhi\omega} \leq v^{\text{storEN}}_{bi}, \quad y^{\text{chrg}}_{bhi\omega} \leq v^{\text{storPW}}_{bi}, \quad y^{\text{dischrg}}_{bhi\omega} \leq \rho_b v^{\text{storPW}}_{bi},$$
$$b \in \mathcal{B}, h \in \mathcal{H}, i \in \mathcal{I}, \omega \in \Omega.$$

The (non-negative) parameter ρ_b determines a fixed discharge to charge power capacity ratio and allows for specifications of storage technologies where the maximum charging power can be different from the maximum discharge power.

Hydroelectric power generation is modeled with low variable operational cost, but constrains are imposed on the hydro operation to account for water availability in reservoirs and hydroelectric resource potential. For regulated hydroelectric generators, $g \in G^{\text{RegHydro}}$, energy limits given by $\xi^{\text{RegHydroLim}}_{gsi\omega}$, constrain the total production over each season. The constraint is given by

$$\sum_{h \in \mathcal{H}_s} y^{\text{gen}}_{ghi\omega} \leq \xi^{\text{RegHydroLim}}_{gsi\omega}, \; g \in \mathcal{G}^{\text{RegHydro}}, s \in \mathcal{S}, i \in \mathcal{I}, \omega \in \Omega. \tag{2}$$

For every node, the total hydroelectric generation, both regulated and unregulated, is limited in terms of annual energy production

$$\sum_{s \in \mathcal{S}} \alpha_s \times \sum_{h \in \mathcal{H}_s} \sum_{g \in \mathcal{G}^{\text{Hydro}}_n} y^{\text{gen}}_{ghi\omega} \leq \xi^{\text{HydroLim}}_{ni\omega}, \; n \in \mathcal{N}, i \in \mathcal{I}, \omega \in \Omega. \tag{3}$$

The hydroelectric energy limits also depend on the stochastic scenarios, allowing EMPIRE to reflect uncertainty about water availability for power production.

EMPIRE has a simplified network description, only considering import/export links between countries (resembling a net transfer capacity, NTC, representation). Exchange is limited by the (symmetric) capacity for each interconnector, $l \in \mathcal{L}$, given as

$$y^{\text{flow}}_{ahi\omega} \leq v^{\text{tran}}_{li}, \quad l \in \mathcal{L}, a \in \mathcal{A}_l, h \in \mathcal{H}, i \in \mathcal{I}, \omega \in \Omega. \tag{4}$$

The sets $\mathcal{A}_l$ contains the pair of unidirectional arcs which together represents the flow across interconnector l. According to this formulation the exchange between countries is fully controllable within capacity limits, an assumption leading to an overestimation of the network flexibility. In reality, flows in an electric network are determined by physical laws, the network characteristics, and power injections and withdrawals. By neglecting this fact, the dispatch found by the model may result in flows that would deviate significantly from actual flows in an electric network (even violate security constraints), commonly referred to as loop flows. However, this simplification reduces both the data requirements for the gird specification and the computational burden of solving the optimization problem and is commonly used in similar studies (Jägemann et al., 2013; Spiecker and Weber, 2014; Haller et al., 2012).

2.2.3. Capacity investment constraints

There are two types of constraints on generation capacity investments in EMPIRE: limits on possible investments per period for a given technology in a given node, and maximum installed capacity constraints. Their formulations are given in equations (5) and (6), respectively.

$$\sum_{g \in \mathcal{G}_{tn}} x^{\text{gen}}_{gi} \leq \overline{X}^{\text{gen}}_{ti}, \quad t \in \mathcal{T}^{\text{AggTech}}, n \in \mathcal{N}, i \in \mathcal{I}, \tag{5}$$

$$\sum_{g \in \mathcal{G}_{tn}} v^{\text{gen}}_{gi} \leq \overline{V}^{\text{gen}}_{tni}, \quad t \in \mathcal{T}^{\text{AggTech}}, n \in \mathcal{N}, i \in \mathcal{I}. \tag{6}$$

The capacity constraints are given at an aggregate technology level per node, rather than a generator level. The limits encompass a combination of technical, economic, environmental or regulatory constraints, some of which are clearly stated policies, like the Germany nuclear power moratorium from 2022, while others are more intangible, such as a limits on wind power expansion in a given country, or opposition against coal-fired power generation.

Similar constraints to Eq. (5) and (6) are imposed for lines and storages (power and energy) capacity investments and installed capacities (omitted here for brevity). The power and energy capacity investments for storages are sized independently unless additional constraints are imposed. For some storage technologies, such as batteries,[4] we fix one of the quantities as a function of the other by imposing the following constraint for a subset of storages $\mathcal{B}^{\dagger}$,

$$v_{bi}^{\text{storPW}} - \beta_b v_{bi}^{\text{storEN}} = 0, \quad b \in \mathcal{B}^{\dagger}, i \in \mathcal{I}.$$

The parameters β_b is the fixed storage power to energy ratio.

2.3. Stochastic scenario generation routine

A scenario generation routine was developed to construct hourly data series to be used in the EMPIRE operational modeling, as shown in Figure 4. For this purpose multi-annual hourly profiles for load, (onshore/offshore) wind power production and solar photovoltaics (PV) production were collected. Hourly profiles for regulated hydroelectric power production were synthesized using a specialized routine.

In order to preserve auto-correlation and correlation between data series, it was decided that the data used for the scenarios $\omega \in \Omega$ would come from a sample of consecutive hours from historical data, and that, within a scenario, the same hours would be used for all the data series. The samples would be randomly chosen, so that

- each scenario would generally get different data, and
- on average, the mean and variance of the sampled data would match that of the original series.

The following explains the implementation of the scenario generation routine.

The first step involves preparing the raw data series. Let $\{\tau_{*hk}^{\text{type}}\}_{h \in H^{\text{full}}, k \in \mathcal{K}}$ be the annual hourly data profile for a given parameter type (e.g. load, wind, solar PV and hydro profiles) for a number of historic years indexed by a set $\mathcal{K}$. The first index of τ_{*hk}^{type} is an object identifier which relates to the type of the profile. For load series, this index identifies the node, for wind production data it identifies a particular generator. A wild-card sign is used when the data series type is not indicated. The set H^{full} is simply the range $[1, 8760]$, i.e. all hours in a full year, meaning that leap year data is disregarded. Before applying the scenario generation scheme a data pre-processing was conducted:

[4]The coupling between power and energy capacity vary significantly between different energy storage technologies. For pumped-hydro the energy capacity is given by the size and design of the upstream (and possibly downstream) reservoir(s), while the power capacity is for the most part determined by the power generation equipment. Modern utility grade batteries, on the other hand, are delivered as units with pre-specified power and energy capacities determined by the technology and electronics used in the design.

1. If there are missing observations in any of the data series, these are re-constructed by either linear interpolation between the closest available hours, or replicating those values in case the missing observations are at the beginning or the end of the respective series.
2. Make an ordered partition of the set of indices H^{full} into four season sets $H^{\text{full}} = \{H_1^{\text{full}}, H_2^{\text{full}}, H_3^{\text{full}}, H_4^{\text{full}}\}$. The number of elements of each season is equal, i.e. $|H_s^{\text{full}}| = 2190$, for $s = 1, \ldots, 4$.

The scenario generation routine is used to construct base data series $\{\xi_{*h0\omega}^{\text{type}}\}_{h\in\mathcal{H},\omega\in\Omega}$ from the historical data $\{\tau_{*hk}^{\text{type}}\}_{h\in H^{\text{full}},k\in\mathcal{K}}$. The algorithm goes as follows

For every scenario $\omega \in \Omega$

1. Select a random year $k' \in \mathcal{K}$.
2. For each regular season $s = 1, \ldots, 4$
   (a) Sample a random number θ_s between 1 and $2190 - (l + 1)$, where l is the number of hours in the EMPIRE regular season
   (b) Populate the regular hours of base data series $\xi_{*h0\omega}^{\text{type}}$ by setting

$$\xi_{*h0\omega}^{\text{type}} = \tau_{*h'k'}^{\text{type}}, \quad j = 1, \ldots, l, \quad h = j + l \cdot (s - 1), \quad h' = \theta_s + (j - 1).$$

3. Form the first extreme load season by summing up the historical load for all nodes in a given hour $h \in H^{\text{full}}$, for the selected year:

$$\tau_{hk'}^{\text{load}} = \sum_{n\in\mathcal{N}} \tau_{nhk'}^{\text{load}},$$

   (a) Select the hour $\overline{h}$ with the highest load value, i.e. the index $h \in H^{\text{full}}$ corresponding to the maximum element of $\{\tau_{hk'}^{\text{load}}\}_{h\in H^{\text{full}}}$.
   (b) The first extreme season of $\{\xi_{*h0\omega}^{\text{type}}\}$ comprise the data from hours in the interval $[\overline{h} - 2, \overline{h} + 2]$ at the selected year k' of $\{\tau_{*hk}^{\text{type}}\}$.
4. Form the other extreme peak seasons by obtaining the maximum load per node

$$\tau_{nk'}^{\text{peakload}} = \max_{h\in H^{\text{full}}} \{\tau_{nhk'}^{\text{load}}\},$$

   then selecting the $|\mathcal{S}^{\text{peak}}| - 1$ nodes $n_1, \ldots, n_{|\mathcal{S}^{\text{peak}}|-1}$, with the highest load (where $|\mathcal{S}^{\text{peak}}|$ is the number of extreme load seasons). Extreme load season $j+1$ is formed by the hours $[\overline{h}_j - 2, \overline{h}_j + 2]$, where $\overline{h}_j$ is the hour with the highest hour load for node j.

After the procedure had been applied the sampled data profiles $\{\xi_{*h0\omega}^{\text{type}}\}$ were checked to see that they closely match the mean and variance of the respective underlying raw data series. The load and hydro base data profiles were further processed as described in the supplementary information to this article.

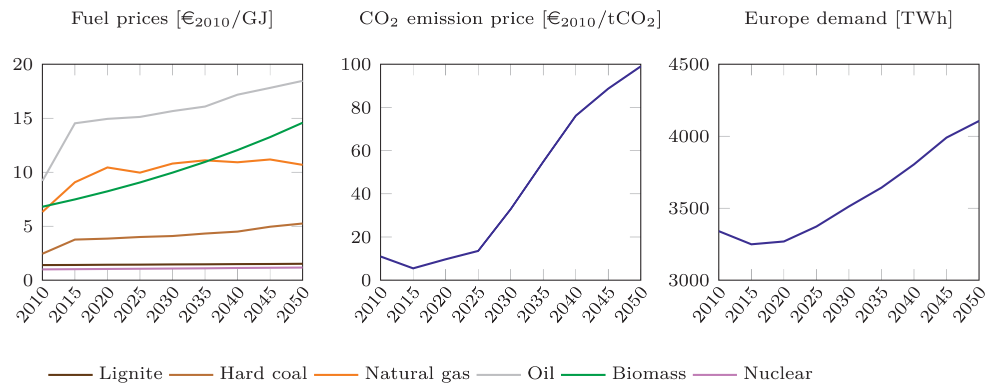


Figure 5: Fuel prices, electricity demand and carbon prices form EU 2013 Reference case. EC (2014) contains prices for hard coal, natural gas and oil. Lignite, uranium and biomass prices come from other sources, (ZEP, 2011; VGB, 2011), and are extrapolated from 2010 data.

3. EU reference scenario case study using EMPIRE

The use of EMPIRE in a decarbonization study for the European power system is illustrated on a data set based on the EU reference case 2013 recently published by the European Commission (EC, 2014). This data set establishes the conditions for the long-term dynamics of the system, such as fuel prices and electricity demand development. A climate policy, in the form of a carbon price, is also collected from the EU reference case. Some of the major assumptions are shown in Figure 5.

In this analysis we use four regular seasons, each with 48 consecutive hours, and six extreme load seasons, each with five consecutive hours. Three stochastic scenarios are used. All in all, this means that for each investment period a total of 666 dispatch hours are considered. Across all the investment periods a total of 5994 dispatch hours are used, establishing a diverse representation of different operating conditions. The supplementary information provided with this paper contains further details regarding the input data used for this analysis.

Two transmission investment cases were developed for the purpose of this study. In the first case maximum capacities for HV line interconnectors were limited to two times their initial capacity, plus an additional 1000 MW per interconnector. By basing the maximum limit on installed capacity, a degree of inertia is introduced in the infrastructure planning, while the 1000 MW addition allows for moderate development of transmission corridors which are not of significant capacity today. For each HV cable interconnector the total expansion was limited to 1400 MW. For every time period the expansion for each HV line interconnector was limited to 10 % of the initial capacity plus 300 MW. For HV cable interconnectors the limit was set to 700 MW per time period. In the second case we did not allow for interconnector expansion.

The following sections presents the results from the two cases, and a discussion.

3.1. Aggregated results for Europe

The European generation capacity and energy mixes for the EU reference case 2013 are displayed in Figure 6 (with interconnector expansion) and Figure 7 (no transmis-

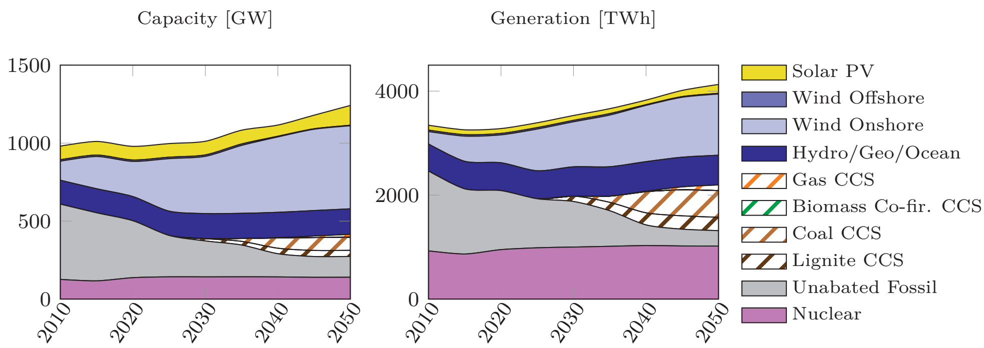


Figure 6: Optimal generation capacity and generation mix in the constrained transmission expansion case. The category Hydro/Geo/Ocean comprises aggregated results for the technologies: hydroelectric power (reservoir and run-of-the-river), geothermal energy and ocean energy. Biomass Co-fir. is a technology where 10 % biomass is cofired with hard coal.

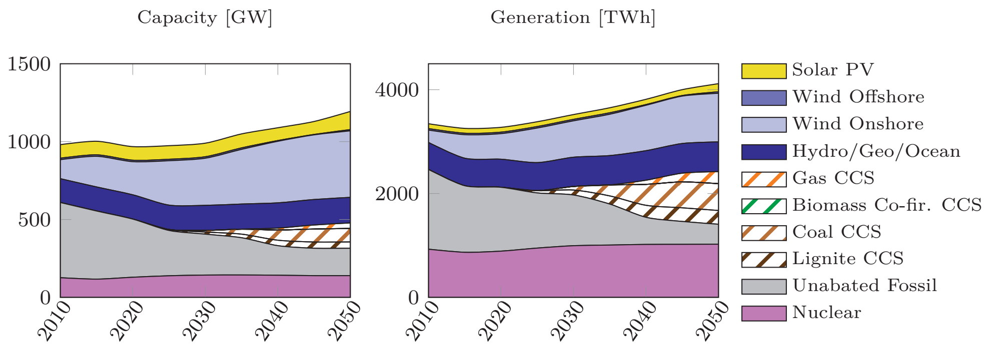


Figure 7: Optimal generation capacity and generation mix in the constrained transmission expansion case

sion expansion). At an European level the differences are not tremendous, but some distinctions are worth pointing out. For onshore wind the installed capacity in 2050 is close to 530 GW in the case with interconnector capacity expansion, about 100 GW higher than in the no expansion case. For solar PV the installed capacity in 2050 is 127 GW in the interconnector expansion case, compared to 117 GW in the no expansion. The additional renewable capacity seen in the interconnector expansion case reduces the need for thermal generation investments. For the no expansion case, unabated and CCS equipped fossil fuel generation capacities are, respectively, 43 GW and 21 GW higher than for the grid expansion case. In the energy mix for the no expansion case, this results in 88 TWh additional generation from unabated fossil generation technologies and 134 TWh more generation from CCS plants. This is offset by 171 TWh onshore wind and some additional generation from other renewables in the interconnector expansion case.

Figure 8 shows the total emissions, average cost of electricity and deployment of CCS and wind generation capacities in Europe. The two cases start to diverge from 2020.

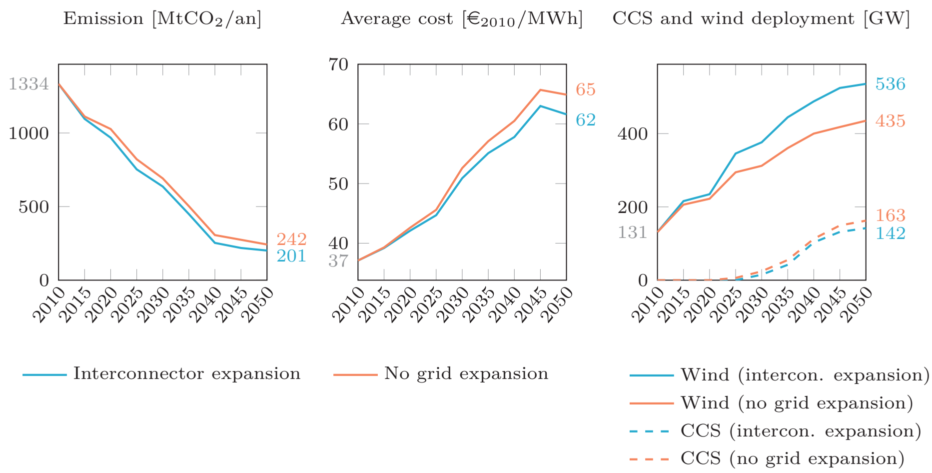


Figure 8: Emissions, average electricity cost and deployment of CCS and wind (onshore/offshore) capacities for the cases with and without interconnector expansion.

Even before the most significant differences in wind investment emerge, there is a gap between the emission trajectories for the two cases. This can be attributed to better utilization of the low-carbon generation capacities as more generation resources can be shared throughout the system. The impact of the increased levels of wind investments is seen to be larger for the average cost. An investigation of the different components of the system costs reveal that the difference is caused by a lower fuel cost in the interconnector expansion case. This is to be expected as wind generation has zero fuel costs. For the CCS capacity the differences between the cases are not considerable, however, the first CCS deployment is delayed by five years, until 2030, in the interconnector expansion case.

3.2. Interconnector expansion

The initial transmission system design and the installed interconnector capacities in the expansion case are shown in Figure 9. In the initial system the total capacity was 67 GW, while the additional interconnector expansion by 2050 ended up at 96 GW, yielding a total of 163 GW capacity for all the interconnectors (we assume no decommissioning of the existing capacities). The constraints imposed on the expansion turn out to be binding for a majority of the connections. A total of 38 out of 55 interconnectors reach the maximum install limit. In particular, all the HV cables links from Norway and Sweden are expanded to the maximum level. The same applies for the HV cables going from the UK to France, Belgium and the Netherlands. The connections along the south-to-north axis going from Spain through France to Germany were also develop to the maximum extent.

Most of the interconnectors with non-binding maximum expansion constraints are found in Eastern Europe and the Balkans. In addition, the links between Germany and Austria, Germany and Switzerland, and Germany and the Netherlands see non-binding constraints.

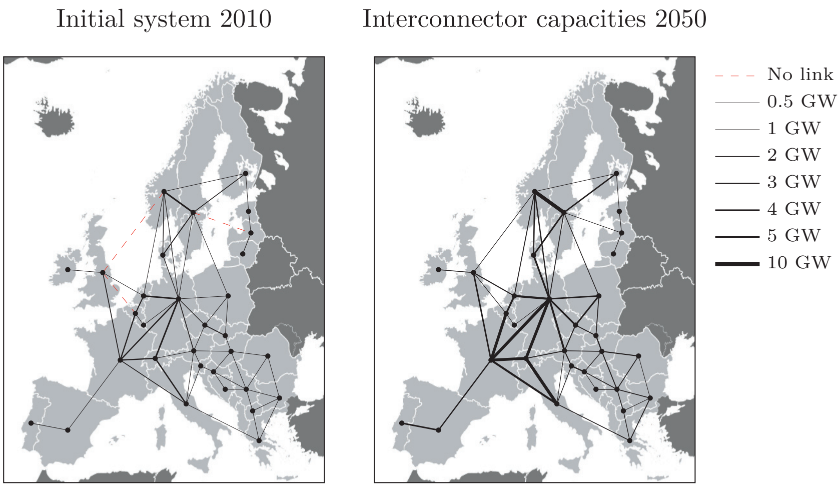


Figure 9: The initial (2010) interconnector capacities and the installed capacities in 2050.

3.3. Generation capacities and energy mix by country

Figures 10 and 11 show the 2050 generation and energy mixes, in the two cases, for the ten countries with the highest electricity demand in Europe. The two cases are generally quite similar. In Germany there is a diverse mix of onshore wind (roughly 50 % of the generation capacity and 20 % of the generation mix) and fossil fueled generation, both with and without CCS. In the generation mix CCS accounts for more than half the total energy produced. In France, nuclear power and onshore wind make up more than 70 % of both the capacity and energy mix. Also, Italy, Great Britain and Spain see significant onshore wind deployment by 2050. In Germany, Italy and Great Britain the maximum install constraints on onshore wind capacity are binding in 2050. In Great Britain and Poland unabated coal and lignite generation are displaced by CCS generation. Significant amounts of natural gas fired CCGTs are used in Germany, Italy, Great Britain, Spain and Belgium.

When it comes to the differences between the two transmission expansion cases the most notable countries are France, Poland and Norway. An additional 40 GW of onshore wind is deployed in France, and 20 GW additional capacity is installed in both Poland and Norway, in the interconnector expansion case. For solar PV the additional capacity in the interconnector expansion case is installed in France (6 GW), Italy (6 GW) and Spain (4 GW), while 5 GW is reduced elsewhere in Europe yielding a net increase of a bit more than 10 GW. The reduces amount of thermal generation capacity in the no expansion case over the alternative is distributed fairly evenly across all countries.

3.4. Discussion

Firstly, even with the current interconnector capacities installed in Europe there is a significant potential for large-scale deployment of onshore wind. The results show a 25 % share in the generation mix for onshore wind without grid investments, and close to 30 % in for the case with. It should be noted that the optimal interconnector expansion found, represents substantial infrastructure investments, an increase of almost 150 % on

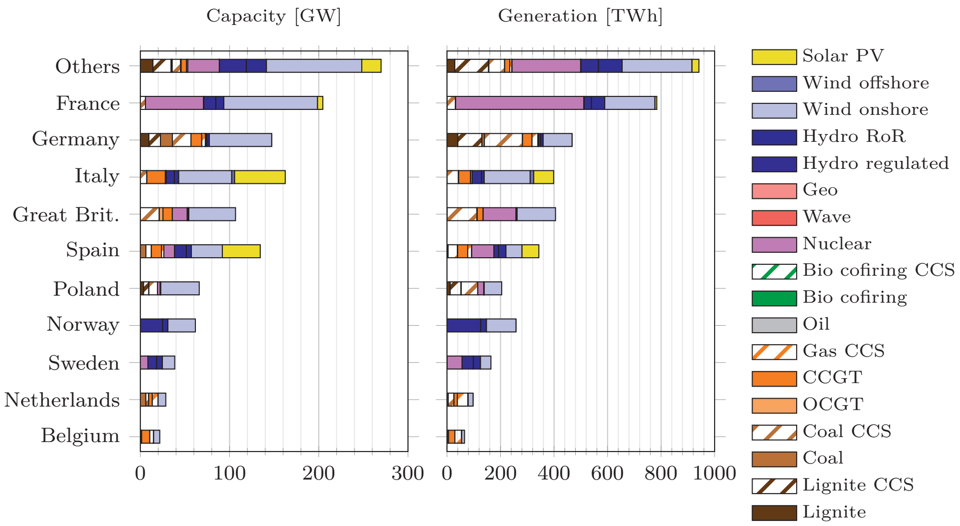


Figure 10: Transmission capacity expansion case: Country-wise Baseline scenario result generation capacity and generation mix in 2050.

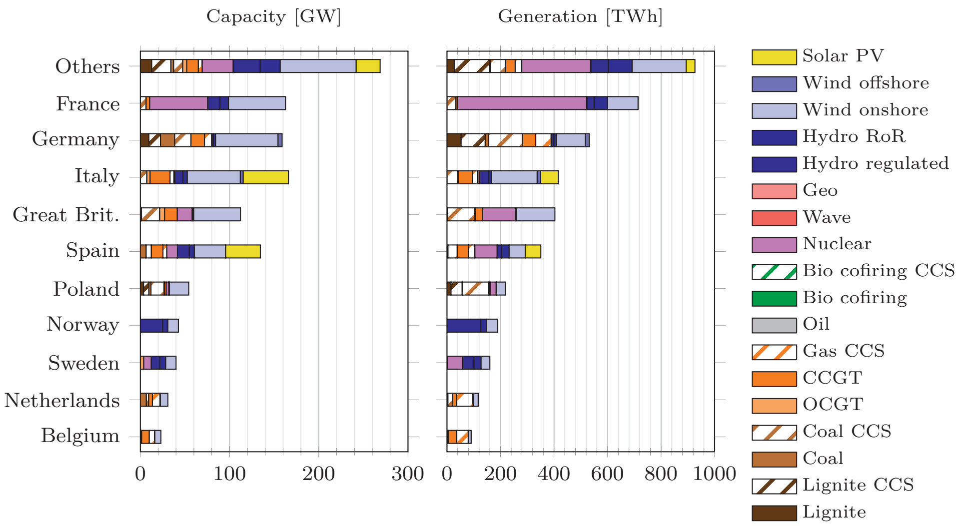


Figure 11: No transmission capacity case: Country-wise Baseline scenario result generation capacity and generation mix in 2050.

top of today's system. For solar PV, on the other hand, the effect of increased exchange capacity was modest. This implies that capital cost reductions are more important for solar deployment than grid investments.

Relative to 2010 levels, emissions are reduced by 85 % in the interconnector expansion case and an 82 % reduction in the no expansion case. Without the ability to increase interconnector capacities more CCS is deployed which essentially leads to more or less the same emission reduction. In terms of costs, however, the differences turned out to be larger. As more wind generation is deployed, accompanied by transmission expansion, less costs are incurred on fuel and carbon. The capital costs are higher, but operational cost savings are high enough to lead to a 5 % net reduction in average cost by 2050, over the no expansion case.

The constraints imposed on maximum investments in generation and transmission capacities turn out to significantly affect the resulting system design. In the case without transmission expansion five of the ten countries with highest demand for electricity experience that the maximum constraints on onshore wind expansion are binding. For the grid infrastructure a majority of the constraints placed on interconnector expansion turned out to be binding. This means that higher investments for both wind and interconnectors would likely have resulted from relaxing these constraints. It can be difficult to determine the appropriate limits to use on investments, however carefully considerations should be used as the results are clearly sensitive to these parameters.

4. Conclusions and further work

This paper provides a full methodological description of EMPIRE, a stochastic investment model for the European power system. The model features multiple investment periods, hourly dispatch modeling for selected time segments of a year and multiple stochastic scenarios representing operational uncertainty. This allows for simultaneous consideration of long-term dynamics, short-term dynamics and short-term uncertainty affecting investment decision and system operation. These are all features which are particularly important when analyzing cases with high penetrations of intermittent renewables as such technologies introduce a great deal of variability and uncertainty in the electricity supply. Computational tractability is achieved by utilizing a multi-horizon tree formulation, in which here-and-now operational decisions are decoupled from future investment and operational decisions.

The case study presented illustrates the use of EMPIRE for a European decarbonization study. Driven by the EU ETS price from the European reference case 2013 an emission reduction of more than 80 % is achieved displacing unabated fossil fuel generation with onshore wind and CCS. By allowing interconnector expansion, more wind power was deployed, which significantly reduces the system operational costs. However only small differences are observed for the total emissions.

There are two natural extensions to the work presented here. Firstly, the current version of EMPIRE does not fully make use of the possibilities of the multi-horizon tree formulation. By incorporating strategic uncertainty, which could for instance affect technology costs, fuel price developments or carbon price development, the effect of long-term uncertainty on decarbonization pathways can be addressed. The second extension of the work is to develop algorithms for efficient solution of multi-horizon models. In particular decomposition methods, such as Benders Decomposition, mixed with parallel computing is a possible approach. By reducing computation times, and distributing computation tasks, it would be possible to considerably increase the number of stochastic operational scenarios used and get a better representation of the variability associated with intermittent renewables. For the levels of wind deployment seen in the illustration cases presented in this paper such considerations are extremely important for determining the need for operational flexibility in the system.

Acknowledgment

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AppendixA. Nomenclature

Table A.1: Paramters and variables in the EMPIRE model

Sets and indices		
Set	Index	Description
$\mathcal{N}$	n	Nodes (country)
$\mathcal{G}$	g	Generators
$\mathcal{L}$	l	Interconnector links (unidirectional)
$\mathcal{A}$	a	Arcs (for directional flow)
$\mathcal{B}$	b	Storages
$\mathcal{H}$	h	Operational hour ($\mathcal{H}^- = \mathcal{H} \setminus \{1\}$), $\lvert\mathcal{H}\rvert = H$
$\mathcal{S}$	s	Season
$\mathcal{I}$	i	Investment time period, $\lvert\mathcal{I}\rvert = I$
Ω	ω	Stochastic scenario, $\lvert\Omega\rvert = O$
$\mathcal{T}$	t	Aggregated generator technologies
$\mathcal{K}$	k	Years for historical data profiles

Decision variables	
Symbol	Description
x^{gen}_{gi}	Generation capacity investment
x^{tran}_{li}	Line capacity investment
x^{storPW}_{bi}	Storage power capacity investment
x^{storEN}_{bi}	Storage energy capacity investment
$y^{\text{gen}}_{ghi\omega}$	Generation
$y^{\text{flow}}_{ahi\omega}$	Line flow
$y^{\text{chrg}}_{bhi\omega}$	Storage charge
$y^{\text{dischrg}}_{bhi\omega}$	Storage discharge
$y^{\text{LL}}_{nhi\omega}$	Energy not supplied (load shed)
$w^{\text{stor}}_{bhi\omega}$	Storage energy content. Charge level = $w^{\text{stor}}_{bhi\omega}/v^{\text{storEN}}_{bi}$
v^{gen}_{gi}	Installed generation capacity
v^{tran}_{li}	Installed transmission capacity
v^{storPW}_{bi}	Installed storage power capacity
v^{storEN}_{bi}	Installed storage energy capacity

Continued on next page

Table A.1 – *Continued from previous page*

Parameters	
Symbol	Description
r	Discount rate
ϑ	Five year scale factor, $\vartheta = \sum_{j=0}^{4}(1+r)^{-j} = \frac{(1+r)^5-1}{r(1+r)^4}$
π_ω	Scenario probability, $\sum_{\omega\in\Omega}\pi_\omega = 1$, $0 \le \pi_\omega \le 1$.
α_s	Seasonal scale factor
c_{gi}^{gen}	Generator investment cost
c_{li}^{tran}	Transmission investment cost
c_{bi}^{storPW}	Storage power capacity investment cost
c_{bi}^{storEN}	Storage energy capacity investment cost
q_{gi}^{gen}	Generator short-run marginal cost
q_{ni}^{voll}	Value of lost load at node
$\xi_{nhi\omega}^{\text{load}}$	Load
$\xi_{ghi\omega}^{\text{gen}}$	Generator capacity availability
$\xi_{gsi\omega}^{\text{RegHydroLim}}$	Max energy production from regulated hydro
$\xi_{ni\omega}^{\text{HydroLim}}$	Max energy production from hydro at node
τ_{*hk}^{type}	Historical data series (type and $*$ indicate data profile type)
$\overline{x}_{gi}^{\text{gen}}$	Initial generation capacity
$\overline{x}_{li}^{\text{tran}}$	Initial transmission capacity
$\overline{x}_{bi}^{\text{storPW}}$	Initial storage power capacity
$\overline{x}_{bi}^{\text{storEN}}$	Initial storage energy capacity
$\overline{X}_{ti}^{\text{gen}}$, $\overline{V}_{ti}^{\text{gen}}$	Generation max build/install capacity (aggregate technology)
$\overline{X}_{li}^{\text{tran}}$, $\overline{V}_{li}^{\text{tran}}$	Transmission max build/install capacity
$\overline{X}_{bi}^{\text{storPW}}$, $\overline{V}_{bi}^{\text{storPW}}$	Storage power capacity max build/install capacity
$\overline{X}_{bi}^{\text{storEN}}$, $\overline{V}_{bi}^{\text{storEN}}$	Storage energy capacity max build/install capacity
i_{*}^{life}	Life time for investment ($*$ used as a wild-card for g, l, b)
η_l^{tran}	Linear line efficiency. Loss $= 1 - \eta_l^{\text{tran}}$
η_b^{chrg}	Storage charge efficiency
η_b^{dischrg}	Storage discharge efficiency
$\eta_b^{\text{roundtrip}}$	Storage round-trip efficiency, $\eta_b^{\text{roundtrip}} = \eta_b^{\text{chrg}}\eta_b^{\text{dischrg}}$
γ_g^{gen}	Generator ramp-up capability
ρ_b	Storage discharge to charge power capacity ratio
β_b	Storage power to energy capacity ratio

Paper E

Paper E

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Modeling transitional measures to drive CCS deployment in the European power sector

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Abstract

The paper presents a modeling study focusing on carbon capture and storage (CCS) as a decarbonization option for European power. In addition, the analysis assesses various support schemes designed to incentivize deployment of demonstration CCS projects. Public grants, feed-in premiums and emission portfolio standards are evaluated. For the analysis, we use a multi-horizon stochastic investment model for the European power system that combines long-term capacity expansion with operational modeling under different load and generation scenarios. The first part of the analysis finds an optimal deployment of 163 GW CCS generation capacity by 2050. The effects of not having a CCS option available are higher emissions, at a higher cost. The analysis of transitional measures shows that co-funding of capital costs is only effective in supporting deployment of demonstration CCS with low fuel costs. Feed-in premiums are found to be the most viable option as it promotes competitiveness of the demonstration plants in the short-term dispatch. The cost of the support schemes had a net present value of 8.7–12.6 bn€ for a 5 GW CCS deployment by 2020. A generator emission performance standard of 225 gCO_2/kWh significantly increased CCS deployment, however, it also resulted in a transitory period with high electricity prices.

Keywords: CO_2 capture and storage (CCS), Demonstration projects, Technology support policies, Energy system planning, Investment analysis, OR in energy

1. Introduction

Europe has set ambitious targets for carbon emission reduction in the coming decades. According to the EU Commission's *Roadmap 2050*, the total domestic emissions are to be reduced by 80 % of the 1990's level by 2050, which implies a more or less full

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decarbonization of the power sector (European Commission, 2011). Carbon capture and storage (CCS) is considered by the EU Commission to be a crucial technology for enabling a cost effective transition to a low carbon European energy system. This was emphasized in the Roadmap 2050 report, and recently confirmed in a separate communication on CCS (European Commission, 2013).

The anticipated potential of CCS in contributing to long-term emission reduction and climate change mitigation globally is highlighted by IEA's scenario analysis in its annual World Energy Outlook publications. The WEO-2012 report finds that in a 450 ppm stabilization scenario, carbon capture and storage contributes to 17 % emission reduction in the energy sector by 2035, compared to the less ambitious New Policies Scenario (IEA, 2012). For comparison, renewables are found to contribute to a 23 % reduction of energy sector emissions. In a special report released in 2013, IEA explored the consequences of delaying large-scale CCS deployment by ten years, from 2020 to 2030, in a 450 ppm scenario (IEA, 2013). Their conclusion was that the additional global cost of power sector decarbonization would amount to more than $1 trillion.

Nevertheless, despite strong political support at an EU level, and recognition by the IEA as an important technology with significant carbon emission reduction potential, CCS for power generation appears to have a bleak future in Europe for the time being. Several large-scale CCS demonstration projects have been on the drawing board (Global CCS Institute, 2014), but to date, not a single one has been initiated and successfully proven the viability of a complete carbon capture, transportation and storage process for use in commercial power generation.[1] Reasons for the disparity between the optimistic expectation and the disappointing reality for CCS over the last decade is discussed in von Hirschhausen et al. (2012). Three factors are highlighted: resistance against structural change in the industry, overly optimistic assumptions regarding CCS in modeling studies and wrong focus in terms of technologies and sectors by policymakers. Although these explanations have merit in retrospectively understanding why CCS has failed to materialize as a possible low-carbon option, there are other issues which are even more relevant for understanding the current challenge of establishing demonstration projects.

The only technology neutral driver for low-carbon investments in Europe today is the EU Emission Trading System (ETS). Through this system a carbon price is generated, which is intended to increase the competitiveness of low-carbon power generation technologies vis–á–vis fossil technologies. However, the price of EU allowances (EUAs) has seen low levels, well below 20 €/tCO_2 (down to 5 €/tCO_2 mid-2013), since the downturn in the European economy began in 2008. Reduction in economic activity in the EU, influx of offsets (emission reduction projects implemented outside of the EU that can be used to reduce allowance requirements) and policies interacting with the EU ETS such as financial support for renewable technologies are cited as reasons (de Perthuis and Trotignon, 2014).[2] Without a sufficiently high price for allowances, CCS simply will not

[1]There are currently two CCS facilities operating in Europe, the Sleipner and Snøhvit CO_2 storage projects. However, both projects are dedicated to natural gas processing, not power generation. In 2014 the Boundary Dam CCS Project in Saskatchewan, Canada, became the first commercial CCS (coal) power plant to come in to operation. The plant can generate 115 MW and utilizes the captured CO_2 for enhanced oil recovery (EOR), creating additional revenue streams. Although the successful deployment of the Boundary Dam project is an important milestone on the road towards commercial scale CCS there is still a need to prove applicability of non-EOR CCS for power generation.

[2]Koch et al. (2014) present an empirical analysis of the strength of various explanatory variables used

be competitive. The exact level needed, however, depends on several factors such as the investment cost of CCS projects. As an indicative result, Lohwasser and Madlener (2012) find, using the European power market model HECTOR, that a level above 30 €/tCO_2 is necessary to support investments of coal CCS if the capital costs are 2500 €/kW or higher (which is in line with the capital costs used in the industry report on CCS costs published by ZEP (2011)). Oei et al. (2014) show, using a model where the CCS transport and storage infrastructure expansion is explicitly optimized, that a carbon price of 50 €/tCO_2 in 2050 only leads to industry using CCS. A carbon price level of 75 €/tCO_2 is needed for CCS to play a role in the power sector.

There have been attempts to establish public co-funding of CCS demonstration projects in Europe. At an EU level, two funding programs have been initiated, the European Energy Programme for Recovery (EEPR) and NER300. Six projects have received support from EEPR while no CCS projects were granted funding in the first application round of the NER300. Lupion and Herzog (2013) provide a detailed account of the political process in the EU to establish funding of CCS demonstration projects, and shortcomings of the NER300 in that respect. By the end of 2014 all but two of the EEPR projects, the Don Valley project in the UK and the ROAD project in the Netherlands have been canceled (Global CCS Institute, 2014).

There are several support mechanisms which can be used for CCS as discussed by Groenenberg and de Coninck (2008) and von Stechow et al. (2011). Investment support programs or a guaranteed price for electricity produced, like the feed-in tariffs received by renewables in Germany, are some possible options to help reduce risk for investors and incentivize development. Other more direct control mechanisms can also be used such as imposing strict emission standards, either for single plants or a portfolio of plants. This has already been adopted in the UK Energy Act 2013 where the limit is set to 450 gCO_2/kWh for new power plants operating as baseload, which excludes unabated coal (Energy Act, 2013). In the US, the Environmental Protection Agency (EPA) established, in its Clean Power Plan (CPP), emission performance rates for coal fired and natural gas fired power plants (Environmental Protection Agency, 2015). The rates are set such that unabated coal plants cannot meet the limit, while efficiently run natural gas combined cycle plants can, even without CCS.[3]

In Europe, CCS stakeholders, comprising utilities, environmental NGOs, research institutions, have formed an association called the European Technology Platform for Zero Emission Fossil Fuel Power Plants (ZEP). In 2012, ZEP published a report recommending a selection of different support schemes to be implemented for CCS in addition to the EU ETS (ZEP, 2012). The message in the report is clear: demonstration projects are a precondition for commercial deployment, and no demonstration projects will be realized without a secure environment for the long-term investments.

In this paper we investigate the potential role of large-scale commercial CCS deployment in a cost efficient decarbonization of the European power sector using an investment

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to understand the EU ETS price collapse. They find that traditional theories such as reduced economic activity, RES support policies and the use of offsets are not sufficient to explain the variation in the EU ETS price. As an alternative, lack of credibility is suggested as a possible cause of the price collapse.

[3]In the CPP the final emission performance rates set by the EPA are 1,305 lbsCO_2/MWh (592 gCO_2/kWh) for existing steam generation units (usually meaning coal fired power plants) and 771 lbsCO_2/MWh (350 gCO_2/kWh) for existing natural gas CCGT units. These limits apply at a state level, and it is up to the state's legislatures to adopt policies to meet them (by 2030).

model optimizing capacity expansion in power systems. The model used is the European Model for Power system Investments (with high shares of) Renewable Energy (EMPIRE), which is a multi-horizon stochastic programming model (Skar et al., 2016). It considers both long-term and short-term dynamics, by incorporating multiple investment periods and sequential hourly market clearing for selected periods of the year. Investment decisions are made subject to uncertainty about future operating conditions, such as load levels and intermittent power generation. The multi-horizon formulation allows for these features to be included simultaneously, without suffering from the curse of dimensionality (Kaut et al., 2014). In order to avoid overly optimistic assumptions favoring CCS, a frequently occurring weakness in previous studies as pointed out by von Hirschhausen et al. (2012), conservative cost estimates developed by ZEP are used. In addition, this study utilizes input data based on the European reference scenario 2013 published by the European Commission (2014), which reflects the currently low levels of the allowance price in the EU ETS. The modeling results show that, driven by carbon price in the EU reference scenario, an emission reduction of more than 80 % is achieved by 2050 compared to 2010 levels, when CCS is available. The total CCS deployment is 163 GW, or a 14 % share of the total installed capacity, in 2050. Without CCS, results show that only a 63 % reduction in emissions are achieved from 2010 to 2050, for the same carbon price.

Following the analysis of the role of commercial CCS in Europe, we present a study of transitional measures to drive investment in demonstration CCS projects. Three mechanisms are modeled in EMPIRE with the goal of deploying 5 GW of CCS capacity before 2025: capital grants, feed-in premium and emissions performance standard. The effectiveness of these measures to spur investments, their cost and potential reception by industry and other stakeholders are evaluated and discussed. Through this analysis we attempt to shed light on what it would take to achieve CCS deployment in Europe, as is the ambition of the European Commission. This can be seen as a complement to the work published in the ZEP report "CO_2 capture and storage (CCS) – Recommendations for transitional measures to drive deployment in Europe", where EMPIRE was also used. Investment subsidies for CCS have previously been analyzed in an European context by Lohwasser and Madlener (2013). In their study, endogenous learning for CCS is implemented in the power market simulator HECTOR, and the effectiveness of different levels of investment subsidies and R&D support on CCS market diffusion are tested. Our study extends the body of research on this field by comparing additional support policies previously not considered in similar studies.

This paper has the following structure: Section 2 introduce the modeling framework used in the analysis along with a description of how the different support mechanisms for demonstration CCS are implemented. Section 3 presents a decarbonization study of the European power sector, with a special focus on the role of CCS. The results from the modeling of transitional measures for demonstration CCS is given in Section 4. Lastly, the conclusions from the two analyses are presented in Section 5.

2. Methodology

The analysis presented in this paper is based on results from EMPIRE. A complete mathematical description of EMPIRE is provided in Skar et al. (2016), while a short description is presented in the following section. Previous use of the EMPIRE includes a study of the European electricity system for several global climate mitigation strategies (Skar et al., 2014), and three studies of CCS potential in Europe by the ZEP market economics group (ZEP, 2013, 2014, 2015).

2.1. EMPIRE – The European Model for Power System Investments with Renewable Energy

EMPIRE is an investment model for the European power system formulated as a multi-horizon stochastic program. A fundamental challenge of investment modeling for large-scale power systems is that the economics of investments are determined by their impact on the system's operation (and cost). Power systems are recognized for having significant heterogeneity in operating conditions, both in a spatial and temporal dimension, which is important to represent in the modeling. As intermittent renewable generation sources, such as wind and solar, continue to increase their share in the energy mix, an increased variability in the short-term dynamics of the power systems is to be expected. The ability to control generation to supply load throughout the system is then reduced. This increases the need for transmission, energy storage and flexible generation technologies. From an investment planning perspective it is difficult to predict how the intermittent generation will correlate with load in the short-term, which introduce uncertainty in the planing. In addition to short-term dynamics there are long-term dynamics to consider as well. Changes in fuel prices and demand for electricity, in particular, are drivers for investments. All these aspects are addressed in EMPIRE by including multiple investment periods (long-term dynamics), multiple sequential market-clearing steps (short-term dynamics) and multiple stochastic scenarios for data affecting the short-term operation of the system (short-term uncertainty). By using a multi-horizon tree formulation we avoid that the optimization problem explodes in size due to the curse of dimensionality. See Kaut et al. (2014) for more detail on the methodology and Skar et al. (2016) for its application to EMPIRE.

The basic structure of the investment and operation decision process in EMPIRE is as follows: for a number of strategic (five year) time periods indexed by $\mathcal{I} = \{1, \dots, I\}$ investments can be made in generation, interconnector and storage capacities. For $i \in \mathcal{I}$ we let the size of the investment in capacity for generator $g \in \mathcal{G}$, where $\mathcal{G}$ is the set of all generators, be x_{gi} and the total costs incurred be c^{gen}_{gi}. For every strategic time period, $i \in \mathcal{I}$, EMPIRE includes an annual economic (spatial) dispatch of the system. In order to reduce the size of the dispatch problem a selected number of dispatch hours $\mathcal{H}$ are considered to represent a year. The set $\mathcal{H}$ is sub-divided into seasons, indexed by $s \in \mathcal{S}$, for which inter-temporal constraints such as ramping and energy storage cycling are enforced in the dispatch. Two types of seasons are considered in EMPIRE, regular seasons and peak load seasons, with different number of hours. The purpose of the regular seasons is to provide a good representation of normal operation of the system, driving the energy mix and accounting for most of the annual operating costs, whereas the extreme load seasons drives the need for installed capacity in high load situations. In EMPIRE investments are made subject to uncertainty about operating conditions in future periods. This is incorporated by considering multiple annual economic dispatch problems with different parameter data, indexed by a finite set Ω. Every stochastic scenario,[4] $\omega \in \Omega$,

[4]The word scenario is used both for data representing long-term dynamics (such as the baseline

is associated with a probability, π_ω. The operational cost associated with the dispatch comprise of annual generation cost, and the cost of energy not supplied (if the system is incapable of satisfying demand at all times). We assume a linear production cost model for generators. The short-run marginal cost (SRMC)[5] of generator $g \in \mathcal{G}$ is denoted by q^{gen}_{gi}, and $y^{\text{gen}}_{ghi\omega}$ denotes its generation output in dispatch hour $h \in \mathcal{H}$ (period $i \in \mathcal{I}$, stochastic scenario $\omega \in \Omega$). In the EMPIRE objective function the *expected* annual operational costs are optimized together with the investment costs (all discounted at rate r).

$$\min_{\substack{\boldsymbol{x}_{i\in\mathcal{I}},\\ \boldsymbol{y}_{i\in\mathcal{I},\omega\in\Omega}}} z = \sum_{i=1}^{I}(1+r)^{-5(i-1)} \times \Big\{ \sum_{l\in\mathcal{L}} CAPEX^{\text{trans}}_{li} + \sum_{b\in\mathcal{B}} CAPEX^{\text{stor}}_{bi} \\ \sum_{g\in\mathcal{G}} c^{\text{gen}}_{gi} x^{\text{gen}}_{gi} + \vartheta \sum_{\omega\in\Omega} \pi_\omega \sum_{s\in\mathcal{S}} \alpha_s \sum_{h\in\mathcal{H}_s} \Big[\sum_{g\in\mathcal{G}} \big(q^{\text{gen}}_{gi} y^{\text{gen}}_{ghi\omega}\big) + \sum_{n\in\mathcal{N}} ENS_{nhi\omega} \Big] \Big\} \quad (1)$$

We use $CAPEX^{\text{trans}}_{li}$ and $CAPEX^{\text{stor}}_{bi}$ to denote costs associated with investment in capacity for interconnector $l \in \mathcal{L}$, and capacity for energy storage unit $b \in \mathcal{B}$, respectively. $ENS_{nhi\omega}$ is used to denote the cost of energy not supplied at node $n \in \mathcal{N}$ for dispatch hour $h \in \mathcal{H}$. Season weights, α_s, $s \in \mathcal{S}$, are used to scale hourly decision variables or parameters (i.e. those indexed by $h \in \mathcal{H}$) to compute their contribution to annual total figure. The factor ϑ scales annual values to five year values, which done since the elements of $\mathcal{I}$ represents five year time blocks.

The dispatch constraints included in EMPIRE comprise of hourly

1. Node load balance constraints (balancing generation, load, storage handling and transmission exchange)
2. Capacity constraints (for generator output, interconnector loading, energy storage charging/discharging)
3. Ramping constraints
4. Storage energy balance constraints

In addition both seasonal and annual energy production from regulated hydro generators are constrained. Capacity investments are also subject to constraints, both in terms of sizing of an investment per period $i \in \mathcal{I}$ and the total installed capacity. Further details, along with the full mathematical formulation of EMPIRE, can be found in Skar et al. (2016). EMPIRE is implemented in the FICO® Xpress Optimization Suite (FICO®, 2015).

2.2. Modeling transitional measures to support CCS in EMPIRE

The following sections describe how the different support policies for demonstration CCS projects are implemented in EMPIRE.

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scenario) and for stochastic data representing uncertainty in the short-term economic dispatch. To distinguish the two types scenarios we refer to the latter case, i.e. data indexed by Ω, consistently as *stochastic scenarios*.

[5]The SRMC includes marginal fuel cost, variable operation and maintenance cost, carbon emission cost and carbon capture and storage cost (when applicable).

2.2.1. *Public grants*

The public grant scheme was represented in EMPIRE by reducing the investment cost parameter for demonstration plants. We let pg_{gi} denote the public grant support and $\mathcal{G}^{\text{demo}}$ the set of all CCS demonstration plants and adjust the investment costs as follows

$$\tilde{c}^{\text{gen}}_{gi} = c^{\text{gen}}_{gi} - pg_{gi}, \qquad g \in \mathcal{G}^{\text{demo}}, i \in \{2,3\}. \tag{2}$$

The adjusted investment cost parameters replace the original cost parameter for demonstration plant investment variables in the objective function Eq. (1). The support is limited to the second and third time blocks of the analysis, starting 2015 and 2020, respectively. The 2015 net present value of the policy cost is the discounted sum of the support paid to demonstration project $g \in \mathcal{G}^{\text{demo}}$, which is pg_{gi} times the investment x^{gen}_{gi}. The expression is given as

$$\text{Public grant scheme cost} = \sum_{i=2}^{3}(1+r)^{-5(i-2)}\sum_{g\in\mathcal{G}^{\text{demo}}} pg_{gi}x^{\text{gen}}_{gi}. \tag{3}$$

2.2.2. *Feed-in premium*

Many European countries have successfully used feed-in schemes to promote renewable generation technologies (Jenner et al., 2013). There are several ways to design a feed-in support system, however it is common to broadly distinguish between feed-in tariffs (FIT), a minimum rate received for electricity produced by a supported generator, and feed-in premiums (FIP), which is a premium paid on top of the electricity price.

In this analysis several versions of a FIP scheme have been evaluated: supporting each demonstration technology with a certain percentage of their short-run marginal cost (SRMC), supporting demonstration projects with a single flat rate and a differentiated support where demonstration gas CCS receives the first type of FIP and lignite and coal receive a flat rate. We also consider the effect choosing one of two different expiry dates for the support scheme.

As with the public grant scheme the feed-in premium policies are implemented by reducing cost coefficients in the objective function, however, these policies affect the variable operational costs. The feed-in premium support is given by fip_{gi}, which gives the following adjusted operational cost

$$\tilde{q}^{\text{gen}}_{gi} = q^{\text{gen}}_{gi} - fip_{gi}, \qquad g \in \mathcal{G}^{\text{demo}},\ i \in \{2,\ldots,I_{\text{fip}}\}. \tag{4}$$

The feed-in premium support is set to last until investment period I_{fip}. The 2015 net present value of FIP support cost is computed as

$$\text{FIP scheme cost} = \sum_{\omega\in\Omega}\pi_\omega\sum_{i=2}^{I_{\text{fip}}}(1+r)^{5(i-2)}\vartheta\sum_{s\in\mathcal{S}}\alpha_s\sum_{h\in\mathcal{H}_s}\sum_{g\in\mathcal{G}^{\text{demo}}} fip_{gi}y^{\text{gen}}_{ghi\omega}. \tag{5}$$

In this expression the product $fip_{gi}y^{\text{gen}}_{ghi\omega}$ is the feed-in premium paid to the CCS demonstration project $g \in \mathcal{G}^{\text{demo}}$ in dispatch hour $h \in \mathcal{H}_s$, in season $s \in \mathcal{S}$, and investment period i. This is scaled by α_s and ϑ to get the total support in investment period i, which is discounted and summed to get the total net present value. Note that this is the *expected* FIP cost over all stochastic operational scenarios used in EMPIRE.

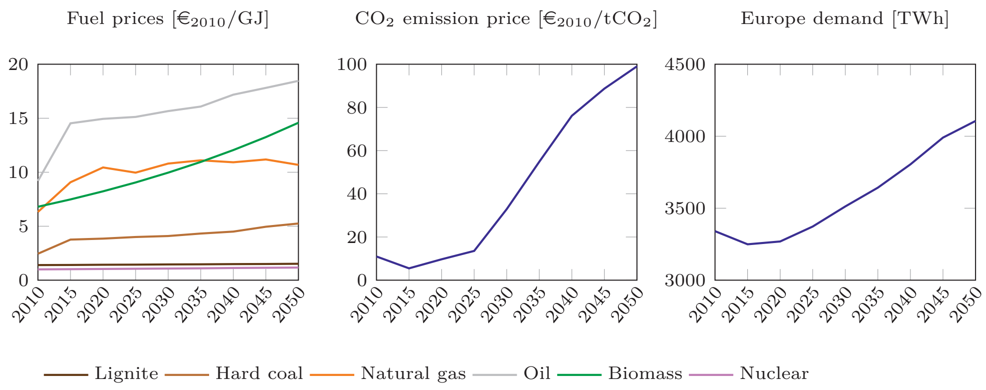

Figure 1: EU 2013 Reference scenario data used by EMPIRE. Fuel prices for hard coal, natural gas and oil have been collected directly from European Commission (2014). The initial lignite price is based on ZEP (2011) and prices of uranium and biomass have been derived from VGB (2011). The price levels are assumed to increase by 1%, 2% and 10% every five years for lignite, uranium and biomass respectively.

2.2.3. Emission performance standard

An emission performance standard (EPS) is a control mechansim which limits the specific emissions, i.e. ratio of emissions to electricity generation, either from indvidual plants or a portfolio of plants. The EPS policies are implemented in EMPIRE using constraints. For individual generators the EPS constraints are

$$(se_{gi} - eps) \cdot y^{\mathrm{gen}}_{ghi\omega} \leq 0, \qquad g \in \mathcal{G}, h \in \mathcal{H}, i \in \mathcal{I} \setminus \{1\}, \omega \in \Omega, \tag{6}$$

where eps is the limit and se_{gi} is the specific emissions for generator $g \in \mathcal{G}$ in year $i \in \mathcal{I}$. This constraint effectively shuts off production from generators for which the specific emissions are higher than the EPS.

The portfolio EPS limit constrains the ratio of total emission to total generation, which can be formulated as follows[6]

$$\sum_{s \in \mathcal{S}} \alpha_s \times \sum_{h \in \mathcal{H}_s} \sum_{g \in \mathcal{G}} (se_{gi} - eps) \cdot y^{\mathrm{gen}}_{ghi\omega} \leq 0, \qquad i \in \mathcal{I} \setminus \{1\}, \omega \in \Omega. \tag{7}$$

3. The least cost route to a decarbonized European power sector

The main scenario developed in this study, our Baseline scenario, is constructed based on data from the EU 2013 Reference scenario (European Commission, 2014). Assumptions regarding fuel prices, carbon price and demand for electricity is shown in Figure 1. This scenario has been selected as it provides an accurate description of current conditions and represents a conservative view of the EU allowance (EUA) price development and electricity demand growth over the coming decade. The low level of the EUA price in the near-term reduces the competitiveness of CCS, which should be included in the

[6] $\sum_{i=1}^{N} a_i x_i / \sum_{i=1}^{N} c_i x_i \leq b \quad \overset{\sum_i c_i x_i > 0}{\iff} \quad \sum_{i=1}^{N} (a_i - c_i \cdot b) \cdot x_i \leq 0$

Table 1: Cost parameters for post-demonstration CCS

	2025	2030	2035	2040	2045	2050
Capital cost [$€_{2010}$/kW]						
Lignite CCS	2600	2530	2470	2400	2330	2250
Coal CCS	2500	2430	2370	2300	2230	2150
Gas CCS	1350	1330	1310	1290	1270	1250
Bio 10pcnt cofir. CCS	2600	2530	2470	2400	2330	2250
Efficiency [%]						
Lignite CCS	37	39	40	41	42	43
Coal CCS	39	40	41	41	42	43
Gas CCS	52	54	56	57	58	60
Bio 10pcnt cofir. CCS	39	40	41	41	42	43
CCS T&S cost [$€_{2010}/tCO_2$]	19	18	17	15	14	13

analysis in order not to be overly optimistic. From 2030 to 2050, the EUA price is shown to increase, reflecting progressive stringency in the EU ETS. Demand for electricity is also shown to increase in the same period which is a result of economic development and more reliance on electricity as an energy carrier in the scenario data.

In the Baseline scenario we assume that CCS demonstration plants have been successfully deployed, leading to availability of post-demonstration plants from 2025. The post-demonstration plants experience a gradual reduction in capital costs, heat rate improvements and decrease in CO_2 transport and storage cost. The data used for the post-demonstration plants were provided by participants of ZEP's working group for market economics II in the work leading to the report ZEP (2013). A list of the CCS cost and generation efficiency data used in this analysis can be found in Table 1. Expansion of CCS infrastructure is not considered directly as the capital costs of infrastructure investments are embedded in transport and storage costs used in the operational expenditures of CCS plants. See Oei et al. (2014) for a more thorough analysis of CCS infrastructure in Europe. In this analysis we do not consider investments in new interconnector or energy storage capacities. This entails a very conservative view of future infrastructure development, reflecting possible situations such as strong public opposition to new transmission lines. In Skar et al. (2016) the sensitivity of CCS deployment to assumptions regarding grid expansion was evaluated.

3.1. Baseline results

The development of generation capacity and generation mix for the European power sector under the Baseline scenario is shown in Figure 2. EMPIRE computes a significant expansion of onshore wind capacity between 2010 and 2030, from a starting point of 122 GW to just above 300 GW. During the same time-period 360 GW of fossil fuel (lignite, coal, gas and oil) capacity is retired. About 165 GW of new unabated fossil generation capacity is built, in addition to 24 GW of lignite and coal CCS capacity. The first investment in CCS occurs in 2025 when 6 GW of lignite CCS is deployed (4 GW in Germany and 2 GW in Poland). By 2050 all the capacity initially operational in 2010 has been retired, replaced by newer and alternative technologies. The total unabated fossil

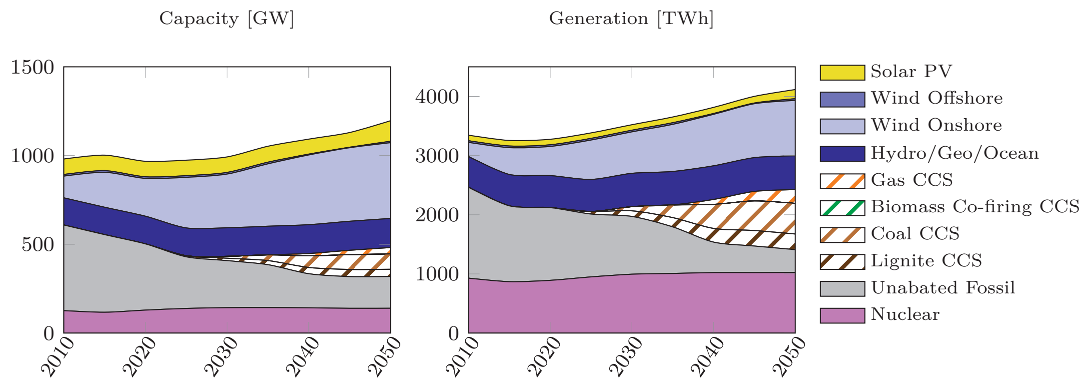

Figure 2: Optimal generation capacity and generation mix in the Baseline scenario.

capacity is 180 GW, which generates 385 TWh of electricity. For CCS technologies the installed capacities are 41 GW for lignite, 86 GW for coal and 36 GW for gas, generating 265 TWh, 517 TWh and 233 TWh, respectively. The total 163 GW of CCS capacity makes up 14 % of the total installed capacity in Europe, while the share of the generation mix is 25 %. Intermittent generation, i.e. wind and solar power, sees an increase of its share in the generation mix, from 11 % in 2010 to 27 % in 2050. The total renewable energy share (including hydro power) ends up at 41 % in 2050.

Results for installed capacity and generation mix for the ten countries with highest electricity demand is shown in Figures 3 and 4, for 2010 and 2050, respectively. Three countries, Great Britain, Germany and Poland, have 50 % of the installed CCS capacity in Europe, with hard coal CCS being the most significant technology. These countries have a total of 53 GW hard coal CCS capacity installed, which makes up a 67 % share of their total CCS capacity. Gas CCS capacity is also fairly concentrated, with the Netherlands, Germany and Belgium being the three countries with highest installed capacity, 63 % of Europe's total.

A useful metric for understanding the competitiveness of different technologies is their capacity factors, the ratio of actual production to the nominal production over a given time period. Investments with high capital costs, such as CCS, typically require a significant utilization to achieve a sufficient return. The Baseline capacity factors for the main fossil fuel technologies are shown in Figure 5. As expected, the utilization of existing capacity decreases as newer and more efficient technologies enter the market. From 2015, newly built unabated lignite and hard coal plants are used as baseload generation, with capacity factors close to 80 %. CCGT plants are used as intermediate generation, with a capacity factor starting at 60 % in 2015. However, as lignite and coal CCS is deployed from 2020 and 2025, the capacity factor for CCGT drops to less than 40 %. Beyond 2035 the conventional coal capacity built after 2010 faces a steep decline in utilization, to less than 20 %. By 2040 the assumed price for carbon has reached a level close to 80 €/tCO_2, which makes the cost of dispatching unabated coal plants prohibitively high during normal operation. This effectively shows a result which might be obvious, but still worth mentioning, even new and advanced coal fired power plants built over the course of the coming decade cannot be expected to be competitive as baseload for more than

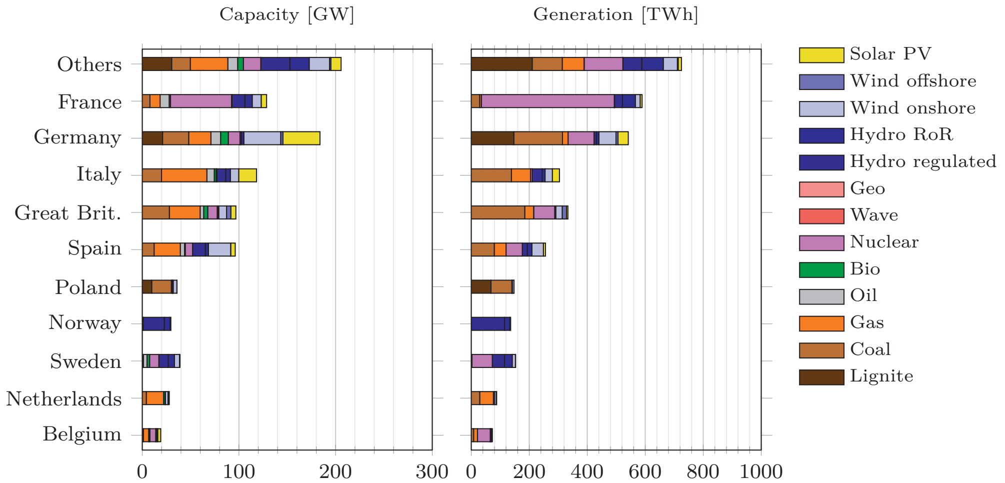

Figure 3: Country-wise Baseline scenario result generation capacity and generation mix in 2010.

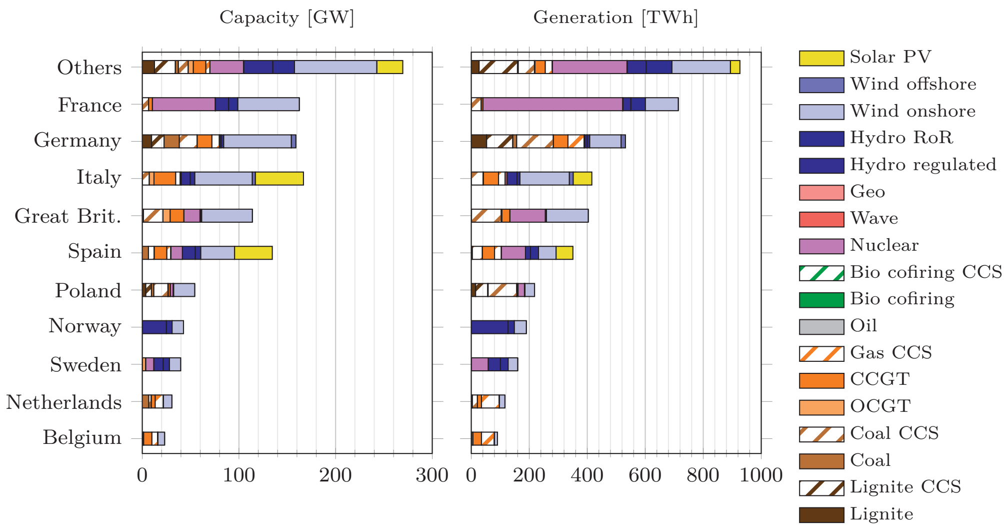

Figure 4: Country-wise Baseline scenario result generation capacity and generation mix in 2050.

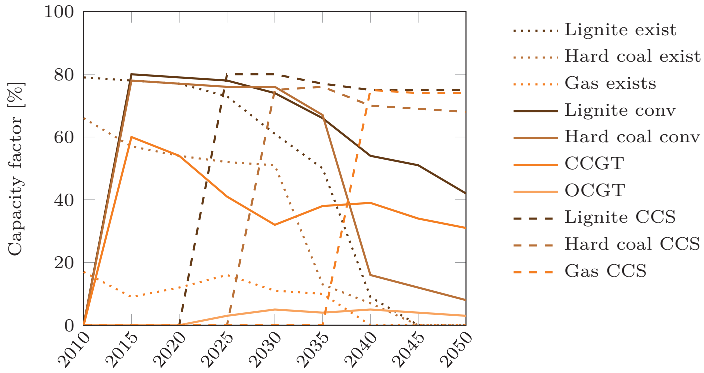

Figure 5: European capacity factors for fossil fuel plants in the Baseline scenario

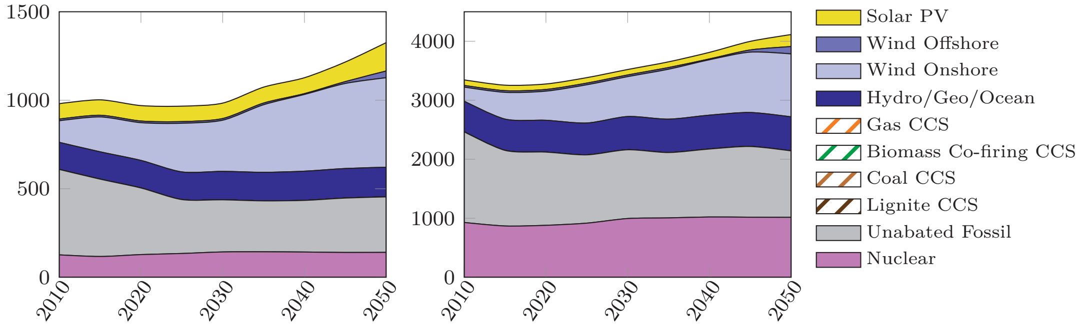

Figure 6: Optimal generation capacity and generation mix in the Baseline-NoCCS scenario

20–25 years, much less than their technical lifetime. All of the CCS technologies that are deployed, immediately enter operation as baseload generation, with capacity factors between 70–80 %.

3.2. Consequences of an absence of CCS as low-carbon option

The Baseline results are, as a result of the principles behind the construction of EMPIRE, the cost optimal development of the European power sector under the EU 2013 Reference scenario assumptions. In order to assess the effect of not having a CCS option available, as an alternative scenario, EMPIRE was setup for an optimization with CCS technologies disabled in a scenario labeled Baseline-NoCCS. The resulting capacity and generation mixes are shown in Figure 6. In this scenario unabated fossil fuel technologies continue to have a reasonably high share in the generation mix. Roughly 25 % of the electricity generated in 2050 comes from unabated fossil plants (mostly natural gas fired CCGTs and OCGTs which account for 70 % of the total fossil generation), 25% comes from nuclear power and remaining generation comes from renewables. A comparsion of pathways for carbon emissions, European average power price and the 2050 system

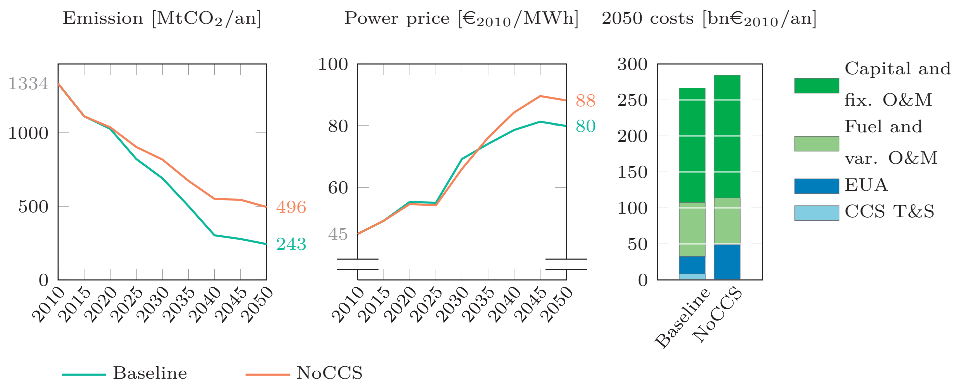

Figure 7: Emission, annual European power price and 2050 annual electricity cost for the Baseline and Baseline No-CCS scenarios.

costs, in the vanilla Basline and Baseline-NoCCS scenarios are shown in Figure 7. The two scenarios diverge from 2025, once CCS is deployed in the Baseline scenario. The Baseline-NoCCS scenario has a less steep emission reduction trajectory than the Baseline scenario, and the total reduction in 2050 relative to 2010 is only 63 % when CCS is not allowed, compared to 82 % when the CCS technologies are available. The power price, found as the average marginal cost of electricity over all countries and hours, is similar for the two scenarios up until 2035. Then the Baseline price starts leveling out and the Baseline-NoCCS price continue to increase for another decade. In 2050 the Baseline-NoCCS scenario has a 10 % higher price for electricity than the Baseline scenario. As the deployment of renewables is higher in the Baseline-NoCCS scenario the fuel costs are significantly lower. However, as the additional cost of covering carbon emissions, and the cost of capacity, are much higher, the total difference in 2050 annual costs between the scenarios is 17.6 bn€. The effect of not having the CCS option is clear, the power sector emissions will be much higher, too high to meet the European Commission's ambitous Roadmap 2050 goals, and at the same time the cost will be higher.

3.3. Related modeling studies focusing on CCS

Over the recent years there have been notable modeling studies done with the focus on the role of CCS in the European sector. Odenberger and Johnsson (2010) applied a capacity investment model, with a detailed electricity generation system description, to assess the optimal development of the European power sector for three different scenarios. Their focus was specifically on the potential of CCS to meet emission reduction targets. In their base scenario, assuming a continued growth of electricity demand and a cap on emissions (85 % in 2050 relative to 1990), the results showed an optimal deployment of 300 GW of coal CCS, capturing 1.8 $GtCO_2$/an, by 2050.

Lohwasser and Madlener (2012) discuss the economics of CCS for coal plants and emhpesises that investment costs are a significantly more important factor than efficiency loss in energy conversion when it comes to economic viablity for coal CCS. The HECTOR model, an electricity market simulation model with endogenous capacity investments, was used to analyse coal CCS deployment in Europe. With assumptions on investment costs and conversion efficiency based on an averages from a wide selection of sources found in an extensive litterature review, the study showed a deployment of 143 GW hard coal generation capcity with CCS by 2030. The investments in CCS are driven by the EU ETS, which in the base scenario is assumed to develop from 20 €/tCO_2 in 2010 to 49 €/tCO_2 in 2030.

Jägemann et al. (2013) use the DIMENSION model to investigate decarbonization scenarios for the European power sector. Restrictions on availability of nuclear power and CCS are explored as alternative assumptions. In their scenario for economic conditions labeled baseline, the additional cumulative system cost over the period 2010 to 2050 of a 80 % reduction target increased by 16 bn€$_{2010}$ when nuclear investments are allowed but CCS is not available. The total installed CCS capacity by 2050 in this scenario is modest, about 40 GW lignite CCS. However, the CCS share of the total generation mix is reported to be 11 %, which is significant. The additional cost of not having CCS when nuclear power is not available is found to be 82 bn€$_{2010}$.

There are several differences in terms of CCS deployment between the different studies. Compared to Odenberger and Johnsson (2010) the baseline results from EMPIRE show a little bit more than half the total CCS deployment. Although the first CCS investments computed by EMPIRE occur in 2025, the total capacity does not exceed 100 GW until 2040, which shows a shift of ten years in time for large-scale deployment compared to Lohwasser and Madlener (2012). The more conservative CCS deployment found by EMPIRE results can be explained by higher investment costs and a carbon price which remains low until 2025. Compared to Jägemann et al. (2013) the total CCS investments computed by EMPIRE are more than four times larger. This can be explained by the fact that nuclear power investments are significantly limited (although available) in EMPIRE, while in the particular scenario where the reported CCS capacity was 40 GW in Jägemann et al. (2013) nuclear power was not restricted.

4. Securing a deployment of 5 GW demonstration CCS by 2020

In the Baseline scenario it is assumed that commercial CCS availability will start at 2025, followed by rapid technology improvement. The realism of such an assumption is of course questionable unless demonstration projects[7] are successfully initiated prior to commercial deployment. In the following we therefore take a closer look at mechanisms for incentivizing CCS demonstration plants.

The amount of capacity eligible for support under the public grant and feed-in premium policies was set to a total of 5 GW. EMPIRE was left free to allocate capacity, up to this limit, between lignite, coal and gas CCS, based on each technology's competitiveness under the given support scheme. In the emission regulation scenario EMPIRE was free to deploy as much of the CCS demonstration projects as it found optimal, albeit without any reduction of cost through support measures.

Three different CCS demonstration project types were included in the modeling, all of which being available from 2015. The investment cost and efficiencies are shown in Table 2. In the Baseline scenario neither of these projects were deployed using their default data.

[7]The analysis in this paper only include CCS projects exclusively for power generation. Applications of CCS in for instance enhanced oil recovery, are not considered.

Table 2: Economic parameters used for CCS demonstration projects in EMPIRE

Project type	Capital cost [$€_{2010}$/kW]	Efficiency [%]
Lignite CCS	2600	31
Coal CCS	2500	33
Gas CCS	1350	48

4.1. Public grants

Public grants, in the form of an upfront payment used to decrease the investment cost of the CCS demonstration plants, were evaluated at levels ranging from 50–200 % of the *additional* CCS capital cost. For conventional, unabated, lignite technology the capital cost is 1600 €/kW, while the cost for demonstration lignite CCS is 2600 €/kW. The public grant schemes therefore would provide a subsidy of 500 €/kW in a 50 % case, 1000 €/kW in a 100 % case and 2000 €/kW in the 200 % case. The same applies for coal CCS, which is modeled with a capital cost of 1000 €/kW above its conventional counter-part. For gas CCS the additional cost (compared to CCGT) is 700 €/kW. In the 200 % support case the support received by gas CCS is actually slightly higher than the total capital cost.

As an illustration, under the 50 % public grant scheme a deployment of 5 GW, divided equally between coal and gas CCS, would cost 850 €/kW, or €2.1 billion in total. To put this number into perspective, the total NER300 budget in the first round was estimated to €1.3–1.5 billion (Lupion and Herzog, 2013). However, as this amount was a result of monetisation of 200 million EU allowances under the ETS, which had lower price than expected (an average sales price of €8.05), the total budget was initially anticipated to be higher. The public grant schemes considered are more expensive than the NER300 program, but still of comparable magnitude.

The results of the EMPIRE optimization of the three public grant schemes show that all support levels lower than 200 % of the additional CCS capital costs are insufficient to incentivize any of the demonstration project types. At a 200 % level, 4.1 GW of lignite CCS capacity is deployed in 2020, at a net present value of 6.5 bn€ in 2015 (discounted from 8.2 bn € in 2020). The capacity factor of the demonstration plants is close to 80 % throughout the analysis, showing that the main obstacle for this particular technology is the capital cost. At a support level of 200 % of additional CCS capital costs, gas CCS would receive 1400 €/kW, 50 €/kW more than the total capital cost. Even this turns out to be insufficient to promote gas CCS, which is a clear argument to consider operational support to improve competitiveness.

4.2. Feed-in premium

Results from the feed-in premium analysis done with EMPIRE are shown in Table 3. There is a clear pattern emerging from the different cases in how the reaction is to the different FIP designs. For the SRMC based FIP, gas CCS becomes competitive before lignite and coal. This is not surprising considering that the investment cost for gas CCS is substantially lower than the other technologies, while the operational costs are high. Limiting the support to only last until 2030 has an adverse effect as it increases the support required to spur investments, making the net present value of the support scheme

Table 3: Results from FIP scheme EMPIRE optimizations. An asterisk is used to label deployment which partly or fully occurs in 2015, while unlabeled results occur in 2020.

Type							
Flat [€/MWh]	SRMC [%]	End	Gas [GW]	Lignite [GW]	Total [GW]	2015 NPV [bn€]	LCOS [€/MWh]
	45.0	2030	No deployment				
	50.0	2030	1.9*		1.9	6.6	40.0
	55.0	2030	5.0*		5.0	20.9	43.7
	30.0	2050	No deployment				
	35.0	2050		5.0	5.0	12.6	31.3
20.0		2030	No deployment				
25.0		2030		4.1	4.1	6.2	15.8
10.0		2050	No deployment				
15.0		2050		2.8	2.8	4.0	15.0
17.5		2050		4.1	4.1	6.6	17.5
20.0		2050		5.0	5.0	9.4	20.0
(L) 15.0	(G) 32.5	2050	1.2	2.8	4.1	6.9	18.8
(L) 17.5	(G) 32.5	2050	0.9	4.1	5.0	8.7	18.8

high as it result in expensive payouts closer in time. In order to achieve a deployment 5 GW gas CCS by 2020 we found that either 55 % of the SRMC had to be covered until 2030, or 35 % until 2050. Between 2020 and 2050 the SRMC for demonstration gas CCS is in the range of 87–94 €/MWh, which means that a 35 % support would be in the range of 30–33 €/MWh. The 2015 net present value of these schemes are 20.9 bn€ and 12.6 bn€, respectively. The levelized costs of support (LCOS), the ratio of net present value of support costs to the discounted sum of generation output, are 43.7 €/MWh and 31.3 €/MWh. If the support is less than 45 % (until 2030) or less than 30 % (until 2050), no investment in demonstration projects take place.

For the flat FIP support rate lignite CCS turns out to have an edge over the other technologies. For a support scheme limited to 2030 the level of the support needs to be above 20 €/MWh. A rate of 25 €/MWh is enough to deploy 4.1 GW of demonstration lignite CCS, at a total cost of 6.2 bn€. This is slightly cheaper than the capital grants scheme, with a cost of 6.5 bn€, which achieved the same demonstration CCS deployment. Similarly, a support of 17.5 €/MWh, lasting until 2050, is sufficient to incentivize 4.1 GW of lignite CCS. At a FIP of 20 €/MWh, lasting until 2050, the total demonstration capacity reach the 5 GW limit.

By combining the two types of FIP schemes a mix of lignite and gas CCS projects are deployed. For illustration, two different levels of the flat FIP recieved by lignite CCS, 15 €/MWh and 17.5 €/MWh, was used in combination with a 32.5 % SRMC support for gas CCS (which would be in the range of 28–30 €/MWh). For the lower FIP rate 2.8 GW lignite CCS is realized in Germany. When the FIP rate is set at a level of 17.5 €/MWh for lignite CCS, an additional 1.3 GW is built in Poland. The gas CCS projects are consistently deployed in the Netherlands and Spain.

4.3. Emission performance standard results

EMPIRE was set up to optimize investments for three types of EPS, all implemented from 2015, listed below.

1. 450 gCO_2/kWh for individual generators. Existing plants exempted.
2. 225 gCO_2/kWh for individual generators. Existing plants exempted.
3. 225 gCO_2/kWh for the European generation portfolio.

Of all the unabated fossil generation technologies included in the EMPIRE data set for this analysis, only gas CCGT, with specific emissions of 336 gCO_2/kWh, is premissable in the 450 gCO_2/kWh EPS scheme. Under the regualtion limiting specific emissions to 225 gCO_2/kWh for individual generators only the CCS technologies are able to satisfy the requirement, which essentially makes this a CCS obligation scenario.

Unlike the financial support policies, which just slightly perturbs the overall results compared to the Baseline, the EPS constraints significantly alter the system optimization. Therefore a wider discussion of the overall system results is provided.

Results for European power sector emissions, average power price and total CCS deployment in the EPS scenarios and the Baseline scenario are shown in Figure 8. This reveals that an EPS limit of 225 gCO_2/kWh for individual generators, is sufficiently strict to open the market for deployment of CCS demonstration plants. A total of 10.6 GW of demonstration CCS capacity, of which 9.2 GW is lignite and 1.3 GW is gas, is installed during the 2020 investment period. The 450 gCO_2/kWh limit for individual generators, and the 225 gCO_2/kWh limit for the entire European fleet, on the other hand, only see deployment of post-demonstration plants, starting from 2025. As with the Baseline scenario we do not impose a precondition that demonstration plants need to be deployed in order for the post-demonstration plants to be available, which can, as discussed, be a problematic assumption.

In terms of emission reduction all of the EPS policy scenarios overachieve compared to the Baseline scenario. By 2050, the total reductions of annual emissions relative to 2010 are in the range 86–88 % for the least stringent individual limit 450 gCO_2/kWh EPS for individual generators and the 225 gCO_2/kWh portfolio limit. The 225 gCO_2/kWh EPS for individual generators achieve an emission reduction of 92 %. As existing fossil plants are exempted from the generator EPS policies, the emissions are gradually decreased for these scenarios. The implementation of a portfolio policy, without exemption for existing plants, effectively set an emission ceiling which causes a drastic short-term reduction in emissions. Eventually, when CCS becomes available, the gap between emission trajectories for the portfolio EPS scenario and the Baseline scenario becomes more narrow.

Although the EPS policies are shown to be effective as a supplement control mechanism for reducing emissions from the power sector, the effect they have on the market at the time of their implementation is dramatic. In the scenario with a 225 gCO_2/kWh EPS for individual generators the average European electricity price is 25 % higher than the Baseline scenario in 2015, and close to 65 % higher in 2020, reaching 91 €/MWh. The reason why the effect is strongest in the period after the policy is implemented is that by 2020 more of the generators exempted from the policy is retired. For the other EPS policies the prices are about 10–15 % higher than the Baseline prices in 2015 and 2020. Eventually the EPS scenario prices comes closer to the Baseline price, and by 2050, the

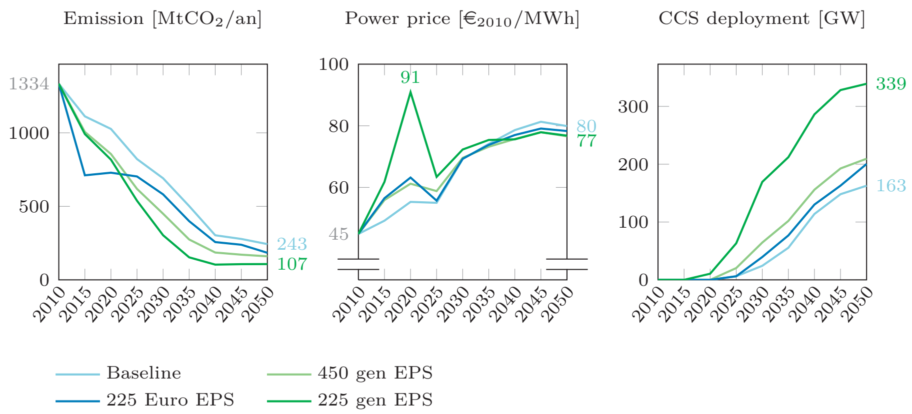

Figure 8: Emissions, power price and CCS deployment for the different EPS policy scenarios.

Baseline price is actually above the policy scenario prices as less EUAs are required to cover emissions.

4.4. Discussion

The reason why public grants fail to incentivize investments for all but lignite CCS is clear when investigating the marginal costs of technologies in EMPIRE. Significant heat rate penalties due to the capture process, along with the additional operational costs associated with carbon transport and storage, force the CCS demonstration plants far behind in the market dispatch. The price of carbon emission is initially low in the Baseline scenario, and therefore these plants loose in competition with conventional plants to enter the dispatch under normal load conditions. When the price of emissions finally does rise to a level such that the demonstration plants become the cheaper dispatch option, compared to conventional technologies, they lose in competition with commercial CCS plants which are then deployed. This highlights an important distinction between renewable technologies and CCS demonstration projects when it comes to financial support and risk. Somewhat simplified one can say that renewables face the risk of receiving a too low price of electricity for its production, making the revenues fall short of covering the required return on capital. The production itself is largely unaffected by market uncertainty, and the revenues earned still offer some return. CCS projects, on the other hand, face the potential risk of becoming stranded assets, in the extreme case not receiving a single cent in return on the investment. This risk is present both for low and high levels of the price on carbon emissions. In particular for large-scale deployment of commercial CCS at high carbon emission prices, there is significant risk of cannibalization of market shares and low utilization of demonstration CCS plants. This effect is, as the modeling results presented here indicate, less significant for technologies with low fuel costs, such as lignite CCS. The reason is simply that lignite CCS is competitive with the commercial coal CCS and gas CCS technologies, and therefore will not be offset by these technologies in the dispatch. However, the most effective policy measure for promoting demonstration CCS, for both lignite CCS and gas CCS, is shown to be operational support, such as a feed-in premium.

The transitional measures tested in the EMPIRE is likely to receive widely different responses from stakeholders. CCS is seen by some environmental NGOs as counterproductive option for reducing emissions, with Greenpeace as the prime example. Slow technological progress, high costs and the risk of leakage from storage sites are typically cited as their primary concern (Greenpeace, 2008). Any form of public financial support of CCS that could potentially divert funding away from renewables will see opposition from groups such as Greenpeace. The power industry on the other hand will be more receptible of a carrot, such as public grants or FIP, rather than a stick approach. Moreover, support can be expected from environmental NGOs advocating for CCS, such as Bellona (Stangeland, 2007).

As discussed by Groenenberg and de Coninck (2008) a CCS obligation would likely not face opposition from environmental NGOs as the policy does not divert public funds from renewable energy projects, however, resistance would probably be large from EU Member States with generation portfolios with high shares of fossil fuels and low potential for carbon storage. In addition, resistance from the power industry due to stranded assets are to be expected, unless some from of grandfathering, in other words exemption of legacy generation assets, is granted as a part of the regulation.

5. Conclusion and Policy Implications

The study presented in this paper adds evidence to support the conclusion reached by several preceding studies of decarbonization pathways for the European power sector, CCS is an integral part of a solution for cost-effective reduction of power generation GHG emissions. The cost and technical parameters used for modeling CCS technologies in EMPIRE, along with assumptions on development of electricity consumption and EUA price, in concert establish a conservative scenario in terms of competitiveness of carbon capture and storage. Still, by 2050, the modeling shows an optimal deployment of 163 GW of CCS generation capacity, and a 25 % CCS share of the total energy mix, divided between different fuel types. Using the EU 2013 Reference Scenario data, the analysis shows that annual emissions are reduced by 82 % from 2010 to 2050 when CCS is part of the total solution. In contrast, the emission reduction achieved with the same carbon price, without CCS available, is just 63 %, at a higher cost.

Realization of demonstration projects is a highly important as a step towards commercialization of CCS, especially for gaining experience in operating CCS plants in the European energy markets and developing the technology further. In the current situation, with a very low EUA price, transitional measures are needed to incentivize first movers on CCS. The three policy mechanisms assessed in this paper, public grants, feed-in premiums and emission performance standards, can all be devised to secure deployment of CCS demonstration projects. For lignite CCS two support schemes, the one based on co-funding of capital cost, and the one with a FIP of 25 €/MWh lasting til 2030, gave virtually the same deployment at more or less the same cost. The cost of the cheapest feed-in premium policies sufficiently generous for a deployment of 5 GW demonstration CCS capacity, is found to be in the range of 8.7–12.6 bn€. Within this range it is possible to achieve 5 GW of lignite CCS, 5 GW of gas CCS or a mix between the two technologies. The analysis illustrates an interesting difference between supporting renewable energy technologies and CCS. Whereas renewable energy naturally enters the dispatch once built, but face the risk of receiving a too low price to cover their capital costs, CCS plants face the risk of not being dispatched at all. This is particularly true for demonstration plants with high fuel costs, as they might be out-competed by unabated fossil generation at low carbon prices and by more efficient CCS if successful commercialization materialize. Operational support is therefore crucial for such projects.

When it comes to emission performance standards as a tool for promoting demonstration CCS it turns out that anything but a CCS mandate on new capacity is not likely to work. Implementing an EPS, either at a generator level or for the European generation portfolio, will push the energy mix in a less carbon-intensive direction, although as a side-effect near-term electricity prices will be high. In particular a CCS mandate policy could make prices sore, up to 64 % above a Baseline scenario in 2020. The difference in price between the Baseline scenario and the CCS mandate scenario evens out eventually, but it is unlikely that a policy causing such a high rise in prices, even if just for a transitory period, can receive the necessary political support to be implemented.

In conclusion, the European Commission's reconfirmation of its support for CCS can, based on this analysis, certainly be argued to be well-founded. Policy support measures securing the economic viability of demonstration projects are urgently needed in order to facilitate a place for CCS as a part of the solution for transitioning the European power sector into a low-carbon future.

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Paper F

Paper F

Bouman, E. A., C. Skar, and E. G. Hertwich. 2016a. “Informing LCA of electricity technologies with a power market model.” Subimtted to an international peer reviewed journal, In review.

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