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Analysis of Investments in Electricity Markets

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Abstract

The ongoing structural transformation of power systems calls for a fundamental overhaul of electricity infrastructure throughout all system components, be it power plants, grids, load management technologies, storage systems or other elements. In the light of the massive changes that the system is likely to undergo within the decades following 2012, it is interesting to study the drivers of investment decisions into various infrastructures to support the power system restructuring. Driven by the increased interest in the economics of power markets, the Thesis performs analysis for investment appraisals to different infrastructure components of future electricity markets. Applications cover a wide range of infrastructure elements such as electric storage, smart grid elements, transmission lines and power plants. The Thesis starts with an introduction into basic concepts of power market economics. Chapter 2 entails an analysis of the use of storage and demand-side-management tools where the sizing of batteries and load control systems is optimized. It follows an investigation of the business case of fast charging stations for electric vehicles. Subsequently, the Thesis includes two chapters on the evolution of fossil-fired power generation capacities where investment incentives under the current power market design are investigated. Since power plant expansion is closely interlinked with grid development plans, the last two chapters are dedicated to the analysis of the interdependency between transmission grids, congestion and investment into generation capacity. Reference is made to recent plans of transmission expansion projects in Germany and Europe.

In all parts of the Thesis, numerical optimization methods are used to approximate the fundamental functioning of markets and derive appropriate investment decisions from these models. Common to all chapters is the use of techno-economic power market analysis where electricity dispatch is optimized in combination with or given some specific capacity decision. The fundamental models are partly casted in complementarity format and some applications do include stochastic elements. The various chapters of the Thesis adopt the perspective of private agents, system operators or social welfare maximizers while the geographical coverage ranges from distribution grid level to European markets.

Keywords:

Electricity, power, investment, grid expansion, power plants, storage, e-mobility

Zusammenfassung

Im Zuge der Energiewende ergibt sich in der Elektrizitätswirtschaft der Bedarf an einer grundlegenden Erneuerung verschiedener Infrastrukturkomponenten. Von Kraftwerken, Übertragungsnetzen, Laststeuerungstechnologien bis hin zu Speichersystemen wird eine große Bandbreite an technischen Lösungen vorgeschlagen um die Systemintegration von erneuerbaren Energien zu fördern. Vor dem Hintergrund der laufenden Umstrukturierung des Stromsektors besteht bei Unternehmen, Politik und Gesellschaft ein erhöhtes Interesse an Analysen zur Wirtschaftlichkeit verschiedener Lösungen. Motiviert durch dieses Interesse, beschäftigt sich die vorliegende Dissertation mit der ökonomischen Bewertung von Investitionen in verschiedene Infrastrukturkomponenten des Strommarktes. Nachdem Kapitel 1 der Arbeit Grundlagen zur Elektrizitätswirtschaft vermittelt, werden im zweiten Kapitel der Betrieb und die Dimensionierung von Speichern und Laststeuerungssystemen in einer Fallstudie optimiert und die Wirtschaftlichkeit der beiden Technologien verglichen. Das darauf folgende Kapitel geht auf die Rentabilität des Betriebes einer öffentlichen (Schnell-) Ladestation für Elektrofahrzeuge ein und untersucht dabei mögliche Geschäftsmodelle für einen profitablen Infrastrukturbetrieb. Zwei weitere Kapitel untersuchen im Folgenden Anreize für Investitionen in fossile Kraftwerke bei Beibehaltung des heutigen Marktsystems mit Grenzkostenpreisen auf Großhandelsmärkten. Die Analyse thematisiert somit die zukünftige Entwicklung des Kraftwerksparks in Deutschland und Europa auch unter dem Aspekt von Unsicherheiten bei Brennstoff- und CO_2-Preisen. Da die Entwicklung des Kraftwerksparks nicht zuletzt auch im Zusammenhang mit den Plänen zum Stromnetzausbau zu sehen ist, sind die letzten zwei Kapitel der Arbeit der Interaktion zwischen Netz- und Erzeugungsausbau gewidmet. Dabei werden aktuelle Planungen zum deutschen und europäischen Netzausbau explizit in die Analyse eingebunden.

Methodisch zeichnet sich die vorliegende Dissertation durch die Nutzung numerischer Optimierungsmodelle in allen Kapiteln aus. Techno-ökonomische Modelle werden verwendet um fundamentale Eigenschaften von Strommärkten nachzubilden und geeignete Investitionsentscheidungen herzuleiten. Eine Gemeinsamkeit aller Kapitel ist die operative Optimierung der Stromproduktion im zeitlichen Verlauf („Dispatch“) bei gegebener oder endogen determinierter Kapazität. Dabei greifen einige Modelle mathematisch auf ein Gleichgewichtsformat zurück und berücksichtigen teilweise stochastische Komponenten. Modellanwendungen behandeln Investitionsentscheidungen aus der Perspektive verschiedener Akteure, darunter private Investoren, Systembetreiber und die öffentliche Hand. Die geografische Dimension deckt in den Anwendungen von Verteilnetzen bis hin zu europaweiten Übertragungsnetzen mehrere Ebenen ab.

Schlüsselworter:

Elektrizität, Strom, Investitionen, Netzausbau, Kraftwerke, Speicher, Elektromobilität

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Content

Abbreviations

aCAES	Adiabatic Compressed Air Storage
AC	Alternating Current
AMM	Advanced Metering System
BC	Brown coal (lignite)
CAPEX	Capital Expenditure
CC	Combined Cycle
CCGT	Combined Cycle Gas Turbine
CCS	Carbon Capture and Storage
CHP	Combined Heat and Power
CO_2	Carbon Dioxide
CPU	Central Processing Unit
CT	Combustion Turbine
DC	Direct Current
DCF	Discounted Cash Flow
DSM	Demand-Side-Management
EC	European Commission
EEV	Expectation with the ExV Solution
EEX	European Energy Exchange
EMF	Energy Modeling Forum
EPEC	Equilibrium Problem with Equilibrium Constraints
EPI	Expectation under Perfect Information
ESS	Expected Value of the Stochastic Solution
EU ETS	European Union Emission Trading System
EU	European Union
EUR	Euro
EV	Electric Vehicle
EVPI	Expected Value of Perfect Information
ExV	Expected Value
GAMS	General Algebraic Modeling System
GT	Gas Turbine
HC	Hard Coal
HVDC	High Voltage Direct Current
IGCC	Integrated Gasification Combined Cycle

IRR	Internal Rate of Return
KKT	Karush-Kuhn-Tucker Conditions
LCoE	Levelized Cost of Electricity
LP	Linear Problem
MCP	Mixed Complementarity Problem
MPEC	Mathematical Problem with Equilibrium Constraints
NEP	Netzentwicklungsplan (Grid Development Plan)
NG	Natural Gas
NLP	Non-linear Problem
NPV	Net Present Value
NREAP	National Renewable Energy Action Plan
NTC	Net Transfer Capacity
OPEX	Operating Expenditure
PC	Pulverized Coal
PhD	Doctor of Philosophy
PTDF	Power Transfer Distribution Factor
PV	Photovoltaic
QCP	Quadratically Constrained Problem
RES	Renewable Energy Sources
ROI	Return on Investment
ST	Steam Turbine
TOU	Time-of-use
TSO	Transmission System Operator
TYNDP	Ten-Year Network Development Plan
VSS	Value of the Stochastic Solution

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Chapter 1 - Introduction

1.1 Motivation and basic literature

The ongoing transformation of the energy system (named "Energiewende" in German) calls for a fundamental overhaul of electricity infrastructure throughout all system components, be it generation capacity, grid capacity, load management technologies, storage systems or other elements. In the light of the massive changes that the system is likely to undergo within the next decades, it is interesting to study the drivers of investment decisions into infrastructure to support the system restructuring.

The increasing use of non-dispatchable Renewable Energy Sources (RES) is one of the major challenges that future energy systems are to tackle. Uncertainty and intermittency[1] of RES feed-in as well as temporal (Sinden 2007) and geographic misalignment (dena 2010) between production and demand increase the need for flexible back-up resources such as storage devices, load management or fast-cycling power plants. Requirements for investment into these sources of flexibility strongly interact with the availability of transmission capacity. Market risks such as fuel cost uncertainties add an additional layer of complexity to investment. All these interactions together make investment analysis a complex question in which quantitative models may help to obtain information on drivers and consequences of investment. All chapters of this thesis contribute with numeric insights into investment valuations as an attempt to identify infrastructure needs and to explain market behavior.

A further complication of investment decision-making and its implementation is the presence of multiple agents in all decision processes. We should recall that although the energy transformation as paradigm shift is a goal imposed by the public, it primarily remains the responsibility of investors to implement the infrastructure in liberalized markets. Models must therefore reflect the decision structures and incentives for private decision-makers. The Thesis performs distinct investment appraisals from the perspective of private agents, system operators and welfare maximizers with applications to different infrastructure components of the future electricity markets. A fundamental question is that of a possible gap between investment requirements and likely realizations. The current market design of liberalized 'energy-only' power markets is on the brink of being reformed so as to provide more incentives for capacity expansion to private investors. Part of the problem is the nature of security of power supply as public good. As users can hardly be excluded from security of supply their willingness to pay for it is low (Stoft 2002). An elaborate overview on the discussion on power market design, "missing money" and "resource adequacy" can be found in Hogan (2005) and Cramton and Stoft (2005). Additionally, Joskow and Tirole (2007) and Littlechild (2006) analyze private sector investment incentives in the light of regulatory instruments such as price caps or the possibility of rationing, concluding that significant under-investment results from regulatory uncertainty and tools such as price caps. Chapter 4 of this Thesis delves into incentives for generation capacity expansion and the role of uncertainty.

Peculiarities of the power sector make investment analysis in electricity markets a specific endeavor different to analysis in classical commodity markets. Short-term balancing requirements as well as technical transmission constraints are among the factors which require quantitative analysis particularly tailored to power markets. There exists a large body of

[1] Uncertainty refers to the non-predictability of feed-in while intermittency designates the chaotic fluctuating pattern that feed-in exposes.

literature that presents introductions to basic concepts in the field of power market economics. The lay reader may be referred to the basic introductory book of Kirschen & Strbac (2004) which has an economic focus with a slight technical touch as it explains fundamental energy engineering principles such as transmission network constraints, financial transmission rights and nodal pricing. Their chapters 7 and 8 present concepts relevant for investment into generation and transmission capacity where the authors present ways of defining optimal capacities taking into account complicating factors such as retiring capacity, cyclical demand and reliability constraints, amongst others. It thereby lays the foundations for much of what is presented in this Thesis. The more advanced reader may be interested in Erdmann & Zweifel (2008) who guide the reader through scientific and engineering basics of energy conversion and the various power generation technologies as well as resource markets. Concepts of probability calculations and some basic investment analysis key indicators (NPV, IRR, ROI, DCF)[2] are presented, which are partly used in this Thesis. Adding to this, the American-based textbook of Stoft (2002) covers key issues of power markets with strong economic focus. As it includes a treatment of market power in the electricity sector in chapter 4 (pp. 337), it is interesting in the context of this Thesis where equilibrium models are used. Theoretic explanations on market power outlined in the Stoft textbook are thus implicitly addressed in this Thesis (e.g. Cost mark-ups, Elasticity of demand, Lerner Index, Herfindahl-Hirschman-Index, Cournot Competition). An advanced and in-depth treatment of equilibrium models - and thus market power - with applications to the electricity sector can be found in Gabriel et al. (2013). The compilation constitutes a good overview of the use of different complementarity model formats in energy economics. While this Thesis does not go beyond the use of Mixed Complementarity Problems (MCP), Gabriel et al. (2013) also present applications of MCP extensions for sequential games, which require a format such as Mathematical or Equilibrium Problems with Equilibrium Constraints (MPEC or EPEC).

Descriptions of the functioning of power markets with dominant technical or techno-economic focus can be found in Konstantin (2007) and Strauss (2009). Konstantin (2007) sets itself apart in that it includes some chapters on concepts relevant for commercial investment analysis and it also entails an interesting chapter on Combined Heat and Power (CHP), a field with increasing importance in future power markets. His chapter 7.2.5 (pp. 287) is highly relevant for this thesis as it encompasses explanations on technical and economic key parameters affecting the economics of power generation. While Konstantin (2007) and Strauss (2009) cover all generation technologies with main focus on fossil-fired generation, Quaschning (2009) provides an overview of renewable energy systems and their technical characteristics. The textbook can be considered as reference work especially in the field of solar and wind energy. In this Thesis, reference to Quaschning (2009) is made on several occasions for the derivation of wind and solar power characteristics.

1.2 Methodology

A multitude of approaches help appraising investment decisions with quantitative models. The Thesis concentrates on so-called ‘fundamental’ market models to approximate the functioning of electricity markets. These do not merely replicate market behavior but they try to explain market behavior by replicating fundamental relationships. Electricity market price modeling is a good example to understand the difference between fundamental and other types of market models. Fundamental models replicate the merit order and technology dispatch to explain the pattern of

[2] NPV = Net Present Value; IRR = Internal Rate of Return; ROI = Return on Investment; DCF = Discounted Cash Flow.

electricity prices while econometric types of models merely replicate prices as close as possible without explaining the underlying technological processes.

The methodological leitmotif of this Thesis is to perform different quantitative applications of infrastructure investment appraisals to case studies in the electricity market. All chapters make use of numerical optimization and equilibrium models which fall into the category of 'fundamental' market models. Several parts of the Thesis deal with decision-making given specific stochastic components, others perform simpler forms of analysis, so-called deterministic optimizations. When categorizing model applications in this Thesis by the representation of uncertainty and the number of model stages, the following methods are applied:

- *(One-stage) Deterministic expected-value problems* – The simplest and most common form of investment analysis is expected-value optimization. It forms part of the realm of deterministic optimization, where uncertain developments are either condensed into average parameters or considered in a separate scenario analysis. Most parts of this Thesis use such simple evaluation models which allow for decent extensions into details other than uncertainty.
- *Two-stage stochastic problems* – Bi-level problems are used in sequential decision-making to distinguish upfront investment decisions from subsequent operational optimizations with stochastic input. A simple example of a two-stage stochastic problem with operational choice between a forward (bilateral) and a spot (pool) trade can be found in Conejo et al. (2010, p.38). When the problem is formulated with 'scenario-variables' (Conejo et al. 2010, p.38), decomposition methods can become particularly interesting to this kind of problems. In some large-scale cases, separate multiple problems are easier to solve in decomposed form rather than in the extensive expected-value form. Chapter 2 incorporates an example of bi-level optimization with Benders decomposition (Benders 1962) where second-stage uncertainties influence first-stage decisions.
- *Multi-stage stochastic problems* – In contrast to single- and two-stage problems, multi-stage optimization takes into account dynamics of uncertainty. Decisions follow a specific sequential order. Constraints ensure that non-anticipativity is guaranteed and so is the decision sequence (Conejo et al. 2010, p.41). A multi-period representation is useful to account for the real options character of investment (Dixit & Pindyck 1994), which confers to the decision agent the flexibility of dynamic adjustment. Multi-stage analysis is thus a tool to scrutinize amount and timing of investment decisions. A major selling point of multi-stage optimization with fundamental models as opposed to econometric-based valuation is that it allows taking into account feedback effects between investment and investment incentives (operational results). Chapter 4 of this Thesis includes multi-period investment decision making under uncertainty.

Decision-making under uncertainty is a field which receives increased interest in applied research due to its importance in real-life power markets. Managing risk and uncertainty in investment decisions is of pivotal importance notably in electricity markets which are characterized by a strong presence of intermittency and unpredictability in both, the long- and short-term context. Over the coming decades, volatility at the production stage is expected to become even more accentuated when electricity is increasingly produced through RES. Stochastic optimization models are therefore suitable for economic analysis purposes in the electricity market. A good overview of advanced methods of stochastic optimization with applications to electricity markets can be found in Conejo et al. (2010). Seminal works on stochastic optimization but without energy focus include Dixit & Pindyck (1994), Birge & Louveaux (1997) and Kall & Wallace (1994). These textbooks complement Conejo et al. (2010)

in the inclusion of mathematical proofs and some examples beyond energy markets while explaining pretty much the same basic concepts.

Independent of the issue of uncertainty, the methodology used for numerical optimizations in this Thesis can also be differentiated by the type of models used. Ventosa et al. (2005) provide an overview of various decision and analysis support models and their possible applications that may help carrying-out investment appraisals. A distinction is made between single-firm optimization models, simulation models, and equilibrium models. The advantage of single-firm optimization models – as used in most chapters of this thesis – is that they allow for representing technical restrictions in great detail. Nevertheless, equilibrium models can also capture technical details to some extent as proven in various applications in Gabriel et al. (2013). A comparison between different forms of equilibrium models is done in Dye et al. (2002) who use the clearing process of the power market model (centralized/decentralized) and the nature of interaction among rival generators (from strong competition to collusion) to distinguish models. A rather methodological way of categorization is to classify models along their problem type (linear, non-linear, integer, complementarity). The problem types addressed in this Thesis are:

- LP (Linear Problem) and NLP (Non-linear Problem) for simple cost minimizations, hence single-firm optimization. Examples of system cost minimizations in power markets can be found in the PhD Thesis of Haller (2012) and Nicolosi (2012). The work of Burstedde (2012) also applies cost minimization and it is in many respects comparable to the model of Chapters 6 and 7 here.
- QCP (Quadratically Constrained Problem) for welfare maximization. The difference between welfare maximization and cost minimization is the inclusion of consumer rents in the social welfare function which makes the mathematical formulation non-linear. However, results from welfare maximization should coincide with cost minimization in perfectly competitive markets without market distortions. Examples of welfare maximizing power market models can be found in Green (2007) and Leuthold et al. (2012).
- MCP (Mixed Complementarity Problem) for profit maximization with multiple players. These types of models are especially interesting when the ability of market power exertion is possible. Examples of applications to electricity markets can be found in Traber & Kemfert (2011a; 2011b) and Weigt & Hirschhausen (2008).

1.3 Applications

In order to cover a wide range of topics within the field of electricity markets, the aforementioned methods are applied to investment analysis in different settings within the electricity market. Distribution grids are addressed as well as transmission grids, mobile and stationary storage and load control, charging infrastructure for electric cars, power plant capacities and transmission grids. These infrastructure components constitute one part of a mosaic of measures to bring forward the energy transformation of the electricity sector.[3] They form part of competitive and partially supplementary solution strategies for the integration of RES into the system. In what follows, a short walk through these options is done one by one.

[3] This list is non-exhaustive. Other flexibility elements could be e.g. curtailment of intermittent RES feed-in or grid congestion management.

In the beginning and the end chapters of this Thesis, electric storage systems are subject of the analysis. Storage has received increasing attention in the electricity community due to its promising role in the integration of RES by increasing temporal flexibility of production and consumption. A broad range of storage technologies co-exist and compete with each other and it remains to be defined which option is the most economic choice from a system perspective. A technology classification can be made by the form in which energy is stored: Electrochemical (batteries), kinetic (flywheels), or potential energy (pumped hydro storage and compressed air storage) (Schill 2011). Other possibilities are the storage of power by the conversion in other materials, for instance in the form of heat via CHP processes, or in the form of hydrogen via electrolysis (Lipman 2011). In the recent past, there is increasing interest in the blending of hydrogen into the existing gas grid (up to ca. 15% blending ratio feasible (dena 2012)) with possible reconversion to power (Sterner 2009). In addition to Table 3 in Chapter 2, a recent overview of storage technologies and possible developments in future can be found in Baker (2008), Hall and Bain (2008), Ibrahim et al. (2008) and the PhD Thesis of Gatzen (2008). These sources give details on technical characteristics as well as the possible evolution of economic viability. Round-trip-efficiency and lifetime appear to be amongst the key technical characteristics affecting economic viability and thus technology choices of investors. Power density and weight are particularly important for mobile storage systems. The most cost-effective options for stationary use currently include hydro pump storage systems, lead-acid and lithium-ion batteries (Electricity Storage Association 2011). Together with the rather visionary concept of Compressed Air Energy Storage (CAES), these storage technologies are treated in the last two chapters of this Thesis. Besides the technology choice, there is also room for investors to play with the sizing a storage system. Investors can modify power rating and storage capacity so as to tailor the system to their needs. Chapter 2 of this Thesis includes a size optimization for a storage system, yet, holding the capacity-power rating ratio constant for reasons of simplicity.

For the integration of RES, storage is one option next to others such as Demand-Side-Management (DSM). DSM refers to the possibility of controlling consumption. Load shedding and load activation are means of interfering with the consumption decision of the consumer with the help of communication technology. Through DSM, consumers with production facilities can be attributed a more pro-active role than in traditional power systems, creating some kind of "prosumer". While there is a lot of talk on 'smart grids' in the electricity community, its large-scale roll-out lags behind expectations in several European countries (Eurelectric 2011, p.28). Exceptions pertain to countries such as Italy and Sweden where regulation is particularly supportive to smart metering roll-out. In most countries, roll-out of DSM systems is progressing slowly in the domain of households and commerce, while load control in industry processes is far more abundant. Paulus and Borggrefe (2011) adopt a system-wide perspective of investment in DSM in a case study for Germany with focus on industrial consumers and they conclude that technical and economic DSM potentials in the energy-intensive industries are promising. However, costs for DSM equipment seem to be too high to compete with other solutions such as flexible back-up power plants (EWI 2012, chap.4.1). In general, DSM may not be suitable for coping with long-term RES intermittency or seasonal balancing but appears more promising for addressing stochastic RES feed-in, i.e. the provision of balancing power (Schill 2011; Strbac 2008).

In the wake of increasing market penetration of Electric Vehicles (EV), it is interesting to analyze possible investment options in this relatively immature market. While extensive analysis has been carried-out on the attractiveness of pure and hybrid EV in comparison to conventional cars (Skerlos & Winebrake 2010; Feng & Figliozzi 2012; Funk & Rabl 1999), little insights have been gained in the economics of corresponding infrastructure. Only few project reports mention costs and conduct commercial evaluations of charging infrastructure (Wiederer & Philip 2010;

Morrow et al. 2008; Slater et al. 2009; Wietschel et al. 2009; PlanNYC 2010). Notably when it comes to investment and operation of battery-swapping stations or fast charging systems, virtually no in-depth analysis has been published besides some analysis of the company TEPCO in Japan (Anegawa 2009; Anegawa 2010). One chapter in this Thesis attempts to contribute insights on this behalf. Japan is currently on the forefront of implementing fast charging infrastructure for EV with the United States following up rapidly. It remains to be seen, whether and where this technology proliferates further. Regarding Germany, the process of market diffusion of EV is mainly steered under the umbrella of the Forum 'Nationale Plattform Elektromobilitaet'. It publishes annual reports on the market situation. While the 2011 report (NPE 2011, p.37) includes an estimate of fast charging facilities of around 250 stations by 2014, the necessity of ca. 7000 stations is mentioned in the long-term vision of the 2012 report (NPE 2012, p.48). This is an ambitious target given barely 12 stations being available in Germany in early 2012 (NPE 2012, p.56).

One strategy to support the integration of RES is seen in the expansion of flexible ("conventional") power generation capacity as sort of back-up facility. This is a rather contentious option since new fossil-fired and nuclear power plants do by virtue of their environmental implications contradict the goal of RES integration at first glance. Some often industry-driven exports, though, purport the requirement of new capacities as back-up. In this context, the BDEW Kraftwerksliste (2011) projects 23.5 GW of reliable capacity to be realized in Germany with high likeliness. The same order of magnitude (19 GW) is indicated by Maurer et al. (2012) as required minimum additional generation capacity for Germany. A report of EWI (2012) projects investments into 44.5 GW gas, and 6.7 GW lignite-fired power plants until 2030. Other sources talk of 8 GW (Knopf et al. 2011) or 10 to 14.2 GW new capacity by 2020 (dena 2008)**.** For Europe, capacity expansion of gas-fired plants (139 GW), coal-fired plants (67 GW) and little nuclear power is projected in the World Energy Outlook (IEA 2011d). EWI (2012) project gas-fueled generation capacity investment to almost double to 55 new GW by 2030 while investment in other conventional resources ought to decline. Two chapters of this Thesis are entirely dedicated to the discussion of the likely evolution of power generation capacities in Germany and Europe. They contribute to discussing the incentives for investment under the current market design of so-called energy-only markets where market prices are marginal cost-based and investors need to recoup investment cost through 'ordinary' power production and sales (no capacity markets exist). It is often argued, that such market design does not provide for sufficient incentives and thus needs some readjustment through some sort of capacity instruments (Cramton & Stoft 2005; Agora 2012; Milstein & Tishler 2012) as implemented in several electricity markets such as PJM[4] and some European countries (Matthes et al. 2012). A compilation of arguments for and against the sufficiency of energy-only markets can be found in Cramton & Ockenfels (2011) and Muesgens & Peek (2011).

Another question is the actual necessity of power generation capacity from a system perspective. This topic can be addressed in technical assessments where system stability requirements and load flows are considered (ENTSO-E 2009). As transmission grids and generation capacity are two interlinked parts of the system, the last two chapters of this Thesis analyze interactions between transmission grid expansion plans and generation capacity expansion.

The need for new transmission grid capacity is almost undoubted in the relevant research community. The 3[d] energy package of the European Commission mandated the European Transmission System Operators (ENTSO-E) to establish a Ten-Year Network Development Plan

[4] PJM refers to a Transmission Operator in the North-Eastern United States. It operates a reliability-pricing model designed to create long-term price signals to attract needed investments in reliability.

(TYNDP) in which specific transmission projects are outlined. It is the first policy effort to bring forward coordinated long-term planning processes for European power transmission infrastructure. The German political situation is characterized by the implementation of the TYNDP through the National Grid Development Plan ('Netzentwicklungsplan'). The ongoing process defines the need for additional transmission capacity within Germany for the next 20 years on a running yearly basis. The June 2012 proposal of the four German Transmission System Operators (TSO) projects the need for around 28 GW of High-Voltage Direct Current (HVDC) lines across Germany by 2032 on top of expansion plans in the Alternating Current (AC) grid (TSO 2012). In the light of past proposals to expand electricity grids, different studies have examined their suitability on an EU-wide scale (Troester et al. 2011; Leuthold et al. 2012; Schaber et al. 2011) and national scale (dena 2010). This Thesis contributes to the discussion with two chapters and it adds some new element in that it covers the most recent HVDC proposals outlined by the German TSO. The plan of July 2012 ('Netzentwicklungsplan') is criticized as being over-dimensioned according to Jarass and Obermair (2012). In late 2012, the Federal Network Agency approved a plan ('Bundesbedarfsplan'), where only 51 of the 74 proposed projects were confirmed, leaving corridor B of the HVDC lines unconfirmed. The 2012 plan now stipulates 2800 km of new lines and 2900 km renewal of lines (Sueddeutsche 2012).

In order to determine the effect of transmission grid expansion projects on the markets, there is a need to apply sophisticated models of power flow simulation. Real world physical flows follow Kirchhoff's and Ohm's laws.[5] Power does not necessarily flow across the shortest distance, but rather it finds its way through the grid via the path of the least resistance. This nature of power flows gives rise to so-called loop-flows in meshed grids. To account for these peculiarities of the power flows, some chapters of this Thesis use a DC load flow approach (Schweppe et al. 1988) for determining power flows in meshed grids. DC Load flow calculations consider only real power equations and can reduce the problem size compared to more realistic AC load flow models (Overbye et al. 2004; Stigler & Todem 2005). Due to the presence of non-linear and non-convex terms in the AC power flow equation, AC load flow models extend a model's calculation time and they tend to have the problem of non-convergence (Groschke et al. 2009). The DC approach aims at approximating real-world AC network flows with a set of linear constraints, which are derived from a range of simplifying assumptions regarding voltage drops. The AC problem is linearized by omitting reactive power flows, normalizing voltages and reducing phase angles.[6] In a case study of the Midwest U.S. transmission grid, Overbye et al. (2004) prove that differences between the DC- and AC-based approaches to nodal pricing are minor. Similarly, Purchala et al. (2005) validate the DC load flow assumptions and testify a good performance but with outliers on individual lines (Burstedde 2012).

Another concept closely related to DC load flow models is that of Power Transfer Distribution Factors (PTDF). These PTDF describe the flow through any individual line in dependence of the input of one unit of electricity at some specified hub. The flow on a specific line is thus determined by all net inputs into all adjacent nodes. Baldick (2002) and Lui & Gross (2002) give theoretical and empirical evidence in favor of the PTDF approximation while Duthaler et al. (2007) highlight approximation errors in zonal models. Errors occur if zones are not defined in line with the fundamental market congestion structure (Burstedde 2012). A further caveat of the PTDF approach is that matrices have to be restated in the case of a change in the network

[5] The Kirchhoff rules define the relation between electric tension and currents: At each node of a network the sum of in- and outgoing flows equals zero and the directed sum of electrical potential differences (voltages) around any closed circuit (loop) is zero. The Kirchhoff rules reformulate Ohm's law which states that the current through a conductor is proportional to the potential difference between two points.

[6] These assumptions are more inaccurate for lower voltage levels and in case of high line usage (Burstedde 2012; Schweppe et al. 1988).

topology. Examples of the use of PTDF can be found in a study on European congestion management policies in Ehrenmann and Smeers (2004), in the PhD Thesis of Waniek (2010), in an application to Re-Dispatch in Germany in Nuessler (2012) and in Linnemann et al. (2011) who use a PTDF approach to incorporate "n-1" security constraints [7] into a re-dispatch model. Overall, Waniek (2010) suggests that the PTDF approach remains popular in research and is preferred to the NTC approach notably in welfare analysis. In this Thesis, the PTDF approach is used in an international model application with welfare analysis in chapters 6 and 7.

An alternative to the AC, DC load flow and PTDF approach is a formulation of flows in a simple piping model, where loop flows are not accounted for. Such approach is used in one chapter of this Thesis, because no aggregated international data on transmission line characteristics (i.e. reactance) was available to the authors. In that case, Net Transfer Capacities (NTC) – as published by ENTSO-E (2012) - can be used as input data. The NTC-approach is a substantial simplification omitting Ohm's and Kirchhoff's physical laws of power flows and its results are not necessarily optimal in the real world. A seminal study which uses NTC values is PRIMES (Capros 2011), the model used for the Energy Roadmap of the European Commission. A hybrid model with both NTC and DC load flow elements (for international and national flows) is presented in Burstedde (2012). The PhD Thesis of Nuessler (2012) tests all approaches: DC, PTDF and NTC-based simulations.

Besides the nature of power flows, there are other peculiarities of the power sector which make quantitative analysis complex. These include the various technical flexibility constraints that come with the necessity of a permanent energy balance. In electricity systems, demand and supply must balance at each instance in time for system frequency to hold. Due to this constraint, the temporal dimension of the dispatch of power generation units is of great importance. Technical constraints such as load gradient limits, start-up limits (Muesgens & Kuntz 2007; Abrell et al. 2008) and economics considerations of ramping costs (Kumar et al. 2012; Lefton & Besuner 2006) must thus be reflected in any economic consideration of power markets. All of the models used in this Thesis do reflect system constraints to account for flexibility of generation. While a realistic depiction requires complex non-linear elements to represent start-up behavior, this Thesis uses the alternative of linearized operational constraints, as proposed in some earlier work (Muesgens & Kuntz 2007; Abrell et al. 2008). A literature overview in Schroeder et al. (2013) includes a compilation of technical and cost figures for power dispatch. Model assumptions in some chapters were aligned with indications in that overview report.[8]

Further issues influencing the model applications and their complexity are the temporal resolution and the time horizon used. The representativeness of results significantly hinges on the use of a fine time resolution and the inclusion of many time steps. To keep a model tractable, representative type-days are often chosen to reflect typical combinations of load and RES feed-in. All chapters of this Thesis use an hourly resolution at the dispatch stage and some representative time horizon. Combined investment-dispatch models in Chapters 4 and 5 use such simplification, as do other comparable investment studies (Nuessler 2012; Haller 2012). Since the choice of a subset of times risks to neglect extreme events, a full year consecutive hourly resolution is sometimes used to model the dispatch in detail (Gatzen 2008; Nicolosi 2012).

[7] "n-1" Security constraints ensure that a system is in a "n-1" secure state. That means an outage of a single component may not trigger cascading failures producing a possible black-out.

[8] The literature review of Schroeder et al. (2013) produces insights into the most recent developments of technical and cost parameters and their likely evolution in the future. CCS and nuclear power appear to be way more costly than assumed in many relevant studies. Another striking fact is that solar power has become much cheaper than most recent studies assume. Regarding the analysis of power plant flexibility, advanced coal- and lignite-fired power plants are almost as flexible as CCGT power plants.

Chapter 7 of this Thesis also uses such fine temporal resolution but compromises on the side of the long-term representation of different years. Nicolosi (2012) demonstrates that the temporal resolution heavily influences the results of investment models in systems with a high share of RES feed-in.

As this Thesis is concerned with investment decisions, the lay reader might expect some introduction into basic notions relevant for general investment analysis such as corporate finance theories and common metrics used for investment appraisals (IRR, NPV, DCF etc.). Since such investment metrics are not at the center stage of this Thesis and to avoid doubling, a short briefing into these concepts is made in the individual sections where they are used.

1.4 Thesis structure

The PhD Thesis has started with an introduction into a number of fundamental concepts relating to electricity markets and methodological basics. In this section, an outline was given for the motivation of the individual chapters and their content. The subsequent chapters of this Thesis are linked by methodological similarities and their focus on investment in electricity infrastructure. Nevertheless, all chapters constitute independent parts one from another. They are enchained by chronological order of production unless otherwise stated.

1
Introduction

2
Smart grid applications in distribution grids

3
E-Mobility charging infrastructure

4
Power plant investment stochastic model

5
Power plant investment in Europe

6
Grid congestion

7
Power plants & grid congestion

Chapter 2 – Smart grids: Storage devices and demand control can contribute to reducing electricity generation cost through inter-temporal substitution of production and demand in a system with a large share of intermittent resources. Chapter 2 presents a model that helps quantifying the related cost reductions in a simulation model of a simplified medium-voltage grid (10kV) under uncertain demand and wind output. A storage and DSM investment decision is considered in a two-stage stochastic program. The model maximizes total welfare and it informs an optimal investment sizing decision as regards specific 'smart grid' applications such as storage facilities and meters enabling load control. The yields vary according to the stochastic realization of wind output and demand. Capacity is chosen to optimize overall expected yield. With this example, the basic foundation of stochastic programming and the advantage of the stochastic programming solution over deterministic approaches are illustrated. In the previous introduction, the fundamental properties of these problems' general class were summarized as two-stage stochastic linear problems with recourse. The resulting problem has two decision stages and a valuable property known as block separable recourse that allows for decomposition approaches to speed up efficient solution. In this special instance, Benders decomposition (Benders 1962) is used. Still, the problem is relatively simple since it forms a linear program, as opposed to more complicated integer programs or complementarity problems, and decomposition therefore happens to not reduce computation time. Furthermore, stochasticity is represented in one single stage, hence the model is not dynamic and no long-term perspectives are included. Later chapters of this Thesis expand on Chapter 2 with long-term dynamics being included.

Topic-wise, chapter 2 deals with the complementarity of different flexibility options (storage, DSM). Results of the stylized application indicate that central storage facilities are a more promising option for generation cost reductions as compared to DSM. This is in line with results from other research in that field and results are corroborated by the fact that large-scale roll-out of metering systems lags behind expectations in most European countries (Eurelectric 2011, p.28). Torriti et al. (2010) provide an overview of the status of demand-side projects in European countries and conclude that DSM has been slow to emerge because of limited knowledge, high costs, and infrastructure. Adding to this, demand shifting has tight time limits and is not suitable for coping with long-term RES intermittency or seasonal balancing (Schill 2011). DSM measures appear more promising for addressing stochastic RES feed-in, i.e. the provision of balancing power (Strbac 2008). The analysis here performs sensitivity tests with respect to the market penetration of uncoordinated plug-in EV which are found to strongly encourage investment into load control equipment and slightly improve the case for central storage devices.

<u>Chapter 3 – E-Mobility infrastructure:</u> The next chapter deals with investment into recharging infrastructure for EV. By now it is fairly uncertain which charging technology for battery-powered EV is going to penetrate the European automotive market. Among the most prominent and most debated solutions are fast-charging stations as well as battery-exchange stations, alongside home-charging. Whilst the necessity of home-charging solutions is undoubted, little knowledge has been spread on the usefulness and the economic rationale of fast chargers. The presented analysis aims at providing a first insight into the economics of this technology which is hitherto little explored research-wise. The work presents cost components, business models and organizational structures of infrastructure management in the case of fast charging for EV. It touches upon metrics used in investment analysis, such as Return on Investment and cost annuities. Calculations of contribution margins allow for an insight into the economics of EV fast charging systems in a short-term perspective. The equilibrium model Esymmetry (Traber & Kemfert 2011a) is used to model the electricity market dispatch under oligopolistic competition of Cournot type. It is used to replicate electricity market prices and to address the question whether market power affects the attractiveness of station operation from the perspective of electric utilities. The results are very pessimistic about the operational margins of station operations and they suggest that charging stations must be complemented with other purposes than pure power sales to generate profits.

<u>Chapter 4 – Power plant investment under uncertainty:</u> Chapter 4 presents an integrated electricity investment and dispatch model with endogenous electricity generation expansion in partial equilibrium format. A modified version of the electricity market equilibrium models Esymmetry and Emelie (Traber & Kemfert 2011a; Traber & Kemfert 2011b) is used to scrutinize power plant investment decisions. Investment analysis under uncertainty is often conducted with options valuation methods. A shortcoming of real options valuation is that interdependencies (feedback effects) between some variable, e.g. electricity market prices, and the investment decision can hardly be modeled, notably in the presence of strategic actions in markets with imperfect competition. In Chapter 4, where power plant investment and subsequent variable dispatch decisions are scrutinized, there is a direct interdependency between fuel and

thus market prices and investment decisions. A real option approach fails to model this link, so another form of multi-period program must be undertaken. Chapter 4 reflects the (real) optional structure of investment but applies a more profound analysis in the stage of the recourse decision, here the dispatch. It hereby allows for modeling feedback of prices on investment in a multi-period setting. Decisions occur at different points in time so that the problem can be viewed as having multiple stages of observations and actions (Birge & Louveaux 1997). The capacity expansion models optimal choices of the timing and levels of investments to meet future power demands. Here, decisions are taken dynamically about additional capacity and about the allocation of capacity to meet demand. The newly integrated model features an hourly time resolution and incorporates long-term fuel price risk at the investment stage. Such stochastic multi-period equilibrium model allows for an outlook on power plant capacity expansion in electricity markets since it adopts the perspective of profit-maximizing electric utilities and it replicates realistic wholesale market prices. The parameterization of an extended model application to European markets is based on a literature review on technical and economic parameters of power generation technologies (Schroeder et al. 2013). An application is done for Germany over the horizon 2010-2035. The model is confined to the German electricity market and it leaves out trade with international partners since the sole purpose of this model is to show how investment behavior changes depending on the problem formulation as either stochastic or deterministic model. The primary focus of the model application in chapter 4 lies on building a stochastic model and the analysis of its properties. It aims at looking into the sensitivities of the model with regard to certain parameters and assumptions and the model structure. A large-scale application of the same model is performed in chapter 5.

Chapter 5 – Power plant investment in Europe: Chapter 5 presents an application of a multi-period deterministic model on power generation capacity expansion in a European-wide context. No uncertainties are considered and compromises are made regarding specific features of the model (time scale, storage) in order to leave space for a large-scale application to Europe for the horizon 2010-2050 where private investors optimize their generation capacity investment and dispatch. Results give indications regarding the expected European power plant mix in the period 2010-2030. It is investigated how different climate policy regimes affect investment and dispatch behavior of the European power markets. The model projects investment into Carbon Capture and Storage (CCS) and nuclear technology to be way lower than comparable peer models do. The model results also show a strict upward movement of wholesale market prices over time. Yet, prices are not high enough to spur large investments into CCS-equipped and nuclear power plants.

Chapter 6 – Grid congestion analysis: This chapter considers transmission grid congestion in a case study of Germany and neighboring countries. After having analyzed incentives for power plant investment (in the previous chapter), it remains to be analyzed how to connect power plants to demand hubs. There has been much talk in recent years about transmission grid infrastructure requirements to connect production and demand. In the light of policy proposals to expand electricity grids so as to better incorporate RES into the system, there is increased interest in quantitative analysis of the congestion situation. Chapter 4 picks up the network regulator’s call for a transmission infrastructure plan and proposes solutions for the horizon 2030 with a focus on the German grid, embedded in a European context. The purpose is to propose a stylized application to European electricity markets. This chapter uses the DC load flow approach in a welfare maximization regime.

Chapter 7 – Power plants & congestion: The literature on power plant placing models is rare. Most model-based investment studies omit the geographical dimension within countries (EWI 2012; EWI et al. 2010) with few exceptions (Frontier & Consentec 2008; Dietrich et al. 2010). Other studies are not model-based (BMU 2010) or capacity expansion is set exogenous (dena

2008). Studies which identify the need for generation capacity as reserve capacities only consider nations as autark power systems but they do not address flexibilities offered through increased international market integration, storage and DSM (EWI 2012; Maurer et al. 2012). The work here proposes the centralized planning of power plant expansion as solution to grid congestion, supported by the increased use of storage, DSM, HVDC lines and international transmission capacities. Dominant power plant technologies and their appropriate placement are identified. The analysis quantifies the added value of centralized planning to overall welfare and puts these into the context of massive grid expansion plans as outlined in the National Grid Development Plan for Germany (TSO 2012). A central conclusion is that HVDC line projects shall be prioritized, as done in the subsequent ‘Bundesbedarfsplan’ (BNetzA 2012).

1.5 Conclusion

This Thesis provides a contribution to the ongoing debate on the restructuring of electricity markets. Quantitative assessments are used to analyze investment decisions into various infrastructure components of the future power system. In what follows, I would like to point to the main findings of the individual chapters, some fundamental policy conclusions and methodological conclusions.

1.5.1 Insights in economic and policy analysis

- The analysis of the second chapter demonstrates a case where investment into storage capacity is likely to be less costly and more useful than DSM systems from an aggregated system cost perspective. Main reasons are the higher flexibility that storage systems allow for, e.g. inter-seasonal storage. When choosing the optimal flexibility tool, investors are therefore likely to favour storage over DSM solutions. This finding is also in line with indications in related work (EWI 2012; Schill 2011; Strbac 2008).
- Chapter 3 on E-Mobility charging clearly shows that fast charging infrastructure can hardly be operated profitably in these early days of EV adoption. Investment and operation of such charging stations must therefore be motivated by other purposes than direct power sales. Additional revenues could e.g. be generated from indirect sales such as parking fees, sales of other goods, and marketing effects.
- Chapter 4 produces insights into the effect of long-term market price uncertainties on investment into fossil-fired power plants. The application is primarily of methodological interest. It is shown that uncertainties have a strong impact on technology choice, decision timing and amount of investment. All in all, uncertainties create expected losses for private investors. Incentives for investment are low especially for oligopolies.
- According to the results of chapter 5, the current market design is not likely to incentivize high amounts of generation capacity investment in European markets. This finding supports the call for a fundamental overhaul of the market design, as energy-only markets appear not capable anymore of providing sufficient incentives for new capacity investment to secure system stability.
- Chapter 6 analyzes the transmission congestion effects of an organised positioning of RES close to demand hubs and alternatively the installation of cross-country HVDC lines. It is found that there continues to be a need for transmission capacity expansion by 2030. However, the strategic placement of generation resources and storage systems could contribute to alleviating the need for large HVDC lines.

- According to the calculations in chapter 7, the HVDC expansion plans of the National Grid Development Plan published in June 2012 appear to be questionable. Adding to the critique of Jarass and Obermair (2012), chapter 7 suggests that the plan proposed by the TSO omits the possibility of increased use of storage and demand-control and the placement of back-up generation capacity. It therefore determines an increased amount of transmission grid capacity requirements. Additionally, the Plan misses to prioritize proposed HVDC projects. The calculations in this chapter demonstrate high differences in the significance of individual HVDC lines. This finding calls for a prioritization of lines. In an amendment to the National Development Plan – posterior to the publication of this work -the Federal Network Agency did indeed reshuffle the list of expansion projects and propose some priorities (BNetzA 2012).

1.5.2 Insights in methodology

- Trials with the decomposition of a linear optimization problem proved hardly useful in the context of a small model application as used in Chapter 2. Troubles to show the advantages of decomposition in terms of computation speed were also stated in related work from presenters at research conferences. If integer-type decisions are embedded in the optimization process, there seems to be some use of decomposition according to recent analysis of Goerner and Abrell (2011) as well as Gunkel and Kunz (2012).
- Chapters 4 and 5 show that modeling markets with equilibrium models and market power exertion under hourly dispatch with inter-temporal restrictions is hardly promising but rather cumbersome computation-wise. Inter-temporal restrictions increase the computation time of the problem dramatically while the market power assumption heavily affects results and produces numerous outliers. The sensitivity of the results regarding market power raises the question whether the actual (moderate) behavior of market power exertion can be truly represented in simple Cournot competition models.
- In chapters 6 and 7, I witnessed CPLEX to be a powerful solver for a large-scale application to European power markets in a non-linear model. I also discovered the usefulness of centralized computers (with parallel computing facilities). Advances in computer technology make it possible to calculate increasingly complex and thus realistic models.
- Chapters 2 and 4 include some form of stochastic optimization. Challenging computation owing to the ‘curse of dimensionality’ in dynamic programming (Birge & Louveaux 1997) limited model complexity and insights into stochastic optimization: However, I have gained a basic understanding of the performance of stochastic models in comparison to deterministic counterparts. This understanding can be useful when applying more advanced methods of stochastic optimization in future.

1.5.3 Perspectives for future research

- This Thesis provides the foundation for future work in several areas. For instance, the model applied in chapters 6 and 7 would benefit from a revamp of the input data. Essentially, the use of more distinguished datasets for countries else than Germany would be needed to draw conclusions about investment behavior outside Germany. Weather-dependent feed-in time series of solar and wind power are amongst the most important datasets to drive results.

- A shortcoming of the works in chapters 2 and 4 is that uncertainty in several input parameters is not represented in great detail. As the treatment of uncertainty is becoming increasingly relevant in many contexts, it should ideally be taken care of with greater sophistication. Extensions of the models could be some more profound econometric underpinnings of stochastic processes through simulated (jointly correlated multivariate) time series and a quantifiable basis for transition probabilities between scenarios. Adding to this, a reflection of risk aversion and particular risk management strategies would make the model representation much more realistic.

1.6 Statement of contributions

The chapters in this thesis are the result of collaborations with the Thesis Supervisors Prof. Dr. Christian von Hirschhausen, Prof. Dr. Claudia Kemfert and additional colleagues, as indicated below. The author of this thesis has made substantial contributions to all chapters covering conceptual design, data compilation, technical model development and writing. The collaborations took on different forms as detailed hereafter.

Chapter 1 - The introduction has not been published elsewhere before. It is my own production.

Chapter 2 - I published chapter 2 as single author paper in Applied Energy. The publication is a result of an earlier collaboration with the TU Berlin students Jan Siegmeier and Murk Creusen. The development of an intial model version was done in collaboration with the TU students while its final implementation and writing of a manuscript has been performed by me.

Chapter 3 - The work on chapter 3 was led by me. Dr. Thure Traber contributed to this work by reviewing the text and assisting in the implementation of the ESYMMETRY model, which has been previously developed by him and Prof. Dr. Claudia Kemfert.

Chapter 4 - The newly developed model is a modification and conjunction of two models (EMELIE, ESYMMETRY) developed by Dr. Thure Traber and Prof. Dr. Claudia Kemfert earlier on. Building on their earlier models, I developed a revamped model and application and produced a paper out of it as single author. I was fully responsible for model programming and implementation. Some input data was taken over from earlier publications of Dr. Traber and Prof. Dr. Kemfert. Most of the input data was updated in accordance with own research.

Chapter 5 - This chapter has been lead-authored by me with significant input from Dr. Thure Traber and Prof. Dr. Claudia Kemfert. Dr. Thure Traber provided the initial model code, also used in chapter 4. While Thure was responsible in renewing some basic features of the model code, I was main responsible for the implementation and analysis of model runs and the writing of the manuscript. Thure and Claudia provided valuable input in fine-tuning the manuscript and graphics as well as coding the model and eventually assisted in the model implementation. The intern Lukas Schmid helped in coordinating with the Energy Modeling Forum (EMF 28).

Chapter 6 - This work results from a study group at Technical University Berlin composed of Jenny Boldt, Lisa Hankel, Lilian Charlotte Laurisch, Casimir Lorenz, Felix Lutterbeck, Pao-Yu Oei, Aram Sander, Helena Schweter, Philipp Sommer and Jasmin Sulerz. I adopted a key role in data compilation, model development, implementation and the writing of the final publication. The work makes use of the ELMOD database on electric grid characteristics available at TU Berlin/TU Dresden. The participating TU students contributed in updating the ELMOD database and reviewing other key input data for the model as well as text writing. The development of a model code from scratch lied in the main responsibility of Pao-Yu Oei and me.

Chapter 7 - The work on chapter 7 is a result of collaboration with Maximilian Bracke, with me as lead author. The work builds in large parts upon the model developed with TU Berlin students in chapter 6 and therefore relies on the ELMOD database of TU Berlin/TU Dresden. Major modifications in model programming, input database and scenarios were performed by me. Maximilian Bracke helped in compiling the literature review.

All chapters of the dissertation are linked to publications in different formats and media, including SSCI-ranked scientific journals. An earlier version of Chapter 2 is published in the Elsevier journal Applied Energy. An earlier version of chapter 3 has led to a published article in Energy Policy. The fourth chapter on power plant investment has produced three publications: One in the proceedings of the conferences EURO 2012, one at the Verein fuer Socialpolitik 2012 and one submission to the journal Energy Systems. A modified version of the text of chapter 5 is submitted to a special issue in the journal Climate Change Economics in the Energy Modeling Forum (EMF 28) framework. The text of the 6th chapter on transmission grid investment was elaborated as policy-oriented paper which is brought to a broad audience through the magazine Energiewirtschaftliche Tagesfragen, a TU Dresden Working Paper, a DIW Wochenbericht, as contribution to the public consultations of the National Grid Development Plan 2012 and as Energy Policy publication. One version of chapter 7 on the integrated planning of power plant expansion and grid congestion is published in the proceedings of the IAEE European Conference 2012 and as DIW Discussion Paper. An overview of publications can be found in the following table.

Chapter 2

Schroeder, Siegmeier, Creusen (2011)	Modeling Storage and Demand Management in Electricity Distribution Grids	DIW Discussion Paper 1110	✓
Schroeder (2011)	Storage and Demand Management in Power Distribution Grids.	Applied Energy, 12, 4700-4712	✓

Chapter 3

Schroeder, Traber (2012)	The Economics of Fast Charging Infrastructure for Electric Vehicles	Energy Policy, 43, 136–144	✓

Chapter 4

Schroeder (2012)	An Electricity Market Model with Generation Capacity Investment under Uncertainty	VfS 2012 and EURO 2012	✓

Chapter 5

Schroeder, Traber, Kemfert (2013)	Energy Modeling Forum 28 model paper	DIW DP and Climate Change Economics subm. 01/2013	subm.

Chapter 6

Boldt et al. (2012)	Renewables in the Grid – Modeling the German Power Market of the Year 2030	TU Dresden WP-EM-48	✓
Schroeder et al. (2012)	In Ruhe planen: Netzausbau in Deutschland und Europa auf dem Prüfstand	DIW Wochenbericht Nr. 20	✓
Hankel et al. (2012)	Stellungnahme zum NEP 2012 Strom	NEP 2012 Stellungnahme	✓
Schroeder et al. (2013)	The Integration of Renewable Energies into the German Transmission Grid - A Scenario Comparison	Energy Policy, 61, p.140-150	✓
Oei et al. (2012)	Szenarienrechnungen zum Netzentwicklungsplan	Energiew. Tagesfragen 9/2012	✓

Chapter 7

Schroeder, Bracke (2012)	Power plant expansion and grid congestion	DIW Discussion Paper 1250	✓

Chapter	**2**	**3**	**4**	**5**	**6**	**7**
Type of model	LP	MCP	MCP	MCP	QCP/ NLP	QCP/ NLP
Objective function	Cost min	Profit max	Profit max	Profit max	Welfare max	Welfare max
Demand function	Linear elastic	Iso-elastic	Linear elastic	Linear elastic	Linear elastic	Linear elastic
Endogenous investment	Storage & DSM	-	Power plants	Power plants	-	Power plants
Competition	perfect	imperfect/ perfect	imperfect/ perfect	imperfect/ perfect	perfect	perfect
Uncertainty	Demand, RES prod.	-	Fuel prices	-	-	-
Grid	DC load flow	-	-	Piping model	DC load flow PTDF	DC load flow PTDF
No. nodes	5	-	-	15	41	41
No. lines	4	-	-	30	231+36	231+36
No. technologies	6	15	15	15+3	6	6
Storage	Pump, battery	-	-	-	Pump	Pump, battery, aCAES
DSM	Household	-	-	-	Household, Commerce, Industry	Household, Commerce, Industry
Time resolution	24h	168h	24h-120h	24h	4 x 168 = 672h	8760h
Reference year	2010	2010	2010	2010	2010	2011
Geo coverage	Local	Germany	Germany	EU27+CH+NO	Subset of Europe	Subset of Europe
Software/ Hardware	GAMS, 32-bit Windows	GAMS, 32-bit Windows	GAMS, 32-bit Windows	GAMS, 32-bit Windows	GAMS, 32-bit Windows	GAMS, 64-bit LINUX
Solver	CPLEX	PATH	PATH	PATH	CPLEX	CPLEX
Related Publications	Schroeder (2011)	Schroeder, Traber (2012)	Schroeder (2012)	Schroeder, Traber (2013)	Boldt et al. (2012) Oei et al. (2012) Schroeder et al. (2012)	Schroeder, Bracke (2012)
Journals	Applied Energy 88 (2011)	Energy Policy 43 (2012)	Verein fuer Socialpolitik 2012; EURO 2012	Subm. to Climate Change Economics EMF 28 Special Issue	Energy Policy forthcom. DIW Wochenbericht En. Tagesfragen 9/2012	DIW DP; Subm. to Energy Systems

Table 1: Overview of models in different chapters

(Source: Own compilation)

Chapter 2 – Storage and Demand-Management in Distribution Systems

2.1 Introduction

Since electricity demand and the availability of output from RES are intermittent by nature, system operators have to resort to relatively costly measures such as reserve energy and re-dispatch to maintain system stability. Back-up capacities are set to become more relevant with increasing shares of RES penetration. In this context, storage devices serve to store excessive electricity generation and feed-in missing energy in times of need. An alternative concept of better aligning demand and supply of electricity through two-way digital communication technology is commonly referred to as 'smart metering'. Measures to manage demand with the help of smart meters include demand response and direct load control. Recent legislation obliges German grid operators and utilities to install smart metering systems in new and refurbished dwellings. While legislative pressure spurs investment in smart metering, it may imply a negative effect on investment incentives in storage.

This analysis scrutinizes load control and storage facilities as potential concurrent options targeting at electricity generation cost reductions and it quantifies possible substitution effects. Because of their common purpose, direct load control and centralised storage are two competing or possibly complementary solutions from the perspective of a vertically integrated power distribution system operator and utility. Moreover, it is tested whether storage and load control could alleviate the need for grid reinforcements by avoiding capacity shortages. The idea is that avoided shortage adds value to storage or DSM devices because of capacity upgrade deferral and added electricity sales (Pudjianto et al. 2006). Additionally to these issues, a methodological purpose of this work is to demonstrate how stochastic optimization and Benders decomposition method can be sensibly applied to analyze and compare investment options in a power distribution system setting. The focus lies on short-term uncertainties and their impact on investment decisions.

There exists a broad range of literature dealing with storage sizing decisions. Diaf et al. (2007), Arun et al. (2008), Kapsali and Kaldellis (2010), Martin et al. (2010) and Troncoso and Newborough (2010) perform numerical optimizations in a deterministic setting. Applications of stochastic patterns of generation and demand can be found in Ekren et al. (2009), Ekren and Ekren (2009), Ekren and Ekren (2010) and Tan et al. (2010). Tan et al. (2010) present a stochastic optimization model of battery sizing for demand control with emphasis on outage probabilities which is not dealt with in this analysis. Roy et al. (2010) apply stochastic wind generation patterns to a wind-battery system sizing model with deterministic demand. IEA (2010) do likewise with Plug-in EV as storage facilities.

The combination of intermittency of RES and DSM is addressed in Moura and de Almeida (2010) and Giannoulis and Haralambopoulos (2011). Concerning DSM, numerous research publications were found on investment decisions into DSM or related operational questions as in Manfren et al. (2011). Lee et al. (2007) assess investment into load management systems for heating in a national case study for Korea. Paulus and Borggrefe (2011) adopt a system-wide perspective of investment in DSM in a case study for Germany with focus on industrial consumers. Neenan and Hemphill (2008) investigate investment from a societal perspective while Strbac (2008) and Electricity Journal (2008) find that investment into DSM appliances might not be all that profitable in general. It is intended to further investigate this claim in the present analysis.

The contribution here is unique in that no study explicitly compares the cost saving potential of storage and DSM in a comprehensive model including grid representation, endogenous investment and factors of uncertainty. Whilst an 11kV distribution network representation in combination with a benefit analysis for storage and demand response measures can be found in Wade et al. (2010), the present work complements their analysis by adding endogeneity to the investment into storage devices and DSM appliances as well as uncertainty of demand and wind generation. A further contribution consists in the application of Benders Decomposition Method to the stochastic program. Decomposition methods can be applied to numerous bi-level optimization problems in the energy sector, such as unit-commitment or capacity expansion. To the author's best knowledge, an application to evaluating storage and DSM infrastructure investment is unprecedented.

The chapter is divided into a descriptive part, including the methodology and model description, an explanation of parameters and scenarios applied. Subsequently, results are outlined, discussed and final conclusions are drawn.

2.2 Model Description

A basic direct current (DC) load flow model (Leuthold et al. 2008) is adapted to a situation with DSM and storage management. The model is designed as linear program under a cost minimization regime with hourly time resolution of two exemplary holidays (winter/summer). It is coded in General Algebraic Modeling System (GAMS) and can be solved with the solver CPLEX (GAMS 2011). A vertically integrated system operator and utility is considered as the cost minimizing agent. As explicated before, the aim of the operator is to reduce generation cost by performing load management through storage and DSM. The agent can decide on whether to invest in storage and DSM technology as well as how to operate it. Still, the operator is able to shift the vertical demand curve left and rightwards through direct load control. The extensive-form cost-minimisation objective reads as follows.

(2.1) Objective (extensive form)

$$\min_{\substack{I_d, I_s,\\ G, D,\\ S_{in}, S_{out}, P}} \sum^{SC} prob(sc) \cdot \sum^{N} \sum^{T} \left[\sum^{S} c_g(s) \cdot G(n,t,sc,s) + I_d(n) \cdot c_d + I_s(n) \cdot c_s \right]$$

The agent minimizes generation cost *($c_g \cdot G$)* of each technology *s* as well as investment cost of DSM *($I_d \cdot c_d$)* and storage *($I_s \cdot c_s$)*. Besides generation and investment, the agent can manipulate storage in- and outflow *(S_{in} and S_{out})*, shed or induce consumption *(D)* and transfer electricity from one node to another *(P)*, subject to constraints detailed below. All variables are positive.

On the demand side, consumers are aggregated at each of the 10kV/0.4kV sub-station nodes *n*. Thus, a diurnal pattern of consumer demand (without DSM and storage), denoted by *q*, can be approximated using standard averaged load profiles weighted by the number of customers at the respective node. A perfectly inelastic, hence vertical demand function is assumed. This is a fundamentally different approach to demand response studies (Aalami et al. 2010; Moghaddam et al. 2011) and suitable here, since the focus lies on the producer side. There is no demand response. The consumer demand *q* is supplemented by contributions from DSM and charging of a battery. Note that demand is treated as stochastic parameter and it thus depends on the set *sc*.

Demand, supply and network flows constitute the energy balance constraint per node (2). It incorporates the simultaneity of generation and consumption as well as the first Kirchhoff rule.

(2.2) Energy balance $\forall\, n,t,sc$

$$\sum^{S} G\,(n,t,sc,s) + S_{out}(n,t,sc) - q(n,t,sc) - D(n,t,sc) - S_{in}(n,t,sc) - \sum^{nn} b(nn,n) \cdot P(nn,t,sc) = 0$$

On the supply side, a setup is considered where each generation technology $s \in S$ at time $t \in T$ and node $n \in N$ contributes an amount G to total electricity generation at marginal unit cost c_g, up to its capacity limit g_{max}, which is exogenous, time-dependent and treated as stochastic parameter.

(2.3) Generation limit $\forall\, n,t,sc,s$

$$g_{max}(t,n,sc,s) - G(t,n,sc,s) \ \geq 0$$

Ideally, investment decisions relating to DSM and storage should consider grid infrastructure constraints because load shifting may serve as a mean to avoid capacity shortage and system outage probability. Pudjianto et al. (2006) explicitly take into account this "delaying capacity replacement" value of DSM devices when appraising the worthiness of DSM. In the model presented here, a number of grid-related constraints are included in order to study the grid impact of storage and DSM operation. The topology of a lossless DC network with L lines is described by the L x N network adjacency matrix lm, where $lm = 1$ means that line $l \in L$ starts at node n, while $lm_{l,nn} = -1$ means that it ends at node nn. Weighting each line with the inverse of its reactance x, the matrix h (4) can be obtained and thus the network susceptance matrix b (5). If the phase angle of node n at time t is denoted by P, the flow along line l at time t is given by equation 6, where the sign of lf depends on the direction of the flow. Since P is defined relative to a reference bus, slackness conditions $slack \cdot P = 0$ hold, and a $slack(1) = 1$ is chosen (that is, $P = 0$) to set node 1 as the reference node (8). Physical line capacity constraints are included (7). In a DC network, only the thermal limit is relevant. If the grid capacity constraint was violated -which turns out not to be the case in this specific application- the operator would incur losses through foregone sales of electricity. Additionally, the capacity shortage is fixed manually ex-post, a penalty cost is applied and the model is re-run with new capacity figures.

(2.4) Weighted Network Matrix $\quad h(l,n) = \frac{1}{x(l)}\, lm\,(l,n)$

(2.5) Network susceptance $\forall\, n$ $\quad b(n,nn) = \sum^{L} h(l,n) \cdot lm\,(l,nn)$

(2.6) Line flow $\forall\, l,t,sc$ $\quad lf(l,t,sc) = \sum^{N} h(l,n,sc) \cdot P(l,n,sc)$

(2.7) Line flow limits $\forall\, l,t,sc$ $\quad -lf_{max}(l) \leq lf(l,t,sc) \leq lf_{max}(l)$

(2.8) Flow convention $\forall\, n,t,sc$ $\quad slack(n) \cdot P(n,t,sc) = 0\,;\ slack(1) = 1$

The second set of constraints relates to DSM. Investments in load control infrastructure for DSM have the benefit of allowing inter-temporal shifts of electricity demand. When direct load control is made possible, parts of electricity consumption may be shifted to earlier or later stages up to power limits d_{neg} and d_{pos}, respectively (9). The system operator does this with the aim of saving cost. d_{neg} represents the power limit of energy that can be saved at each time by shifting load away to another period of the day. Accordingly, d_{pos} is the potential that can be added at each time. Note that both parameters are defined as positive numbers while contributions must balance to zero over time (10). The option for DSM is reflected in an additional contribution to total demand, *D*.

DSM appliances may yield peak load reductions and thereby justify infrastructure reinforcement deferral. However, it is disregarded that the installation of DSM appliances could yield overall demand reductions. This is done not only because projections of demand reduction through DSM devices appear to be fairly uncertain and consumer-specific, ranging between zero and 20% (Papagiannis et al. 2008; EcoFys 2009; Moura & de Almeida 2010). The focus is on direct load control exerted by the system operator. Demand response measures and related consumption savings driven by consumer behavior are beyond the scope of this operator´s cost-minimization model.

Storage facilities in the distribution network can take up a positive charge S_{in} at time t, convert it (with some loss e) and subsequently provide positive amounts S_{out}, where the overall balance is governed by capacity constraints (12) as well as input and output kW power constraints, which are set equal to kWh capacity constraints for reasons of simplicity (13). Note that energy capacity is set equal to power limit and that there is no continuation value of left-over storage since the storage device is empty at the last time period (11).

(2.9)	DSM Limits $\forall\, n, t, sc$	$d_{neg}(n,t) \cdot I_d(n) \leq D(n,t,sc)\,;\, D(n,t,sc) \leq I_d(n) \cdot d_{pos}(n,t)$
(2.10)	Constant total demand $\forall\, n$	$\sum^{SC} \sum^{T} D(n,l,sc) = 0$
(2.11)	Storage balance $\forall\, n, sc$	$\sum^{T} [S_{in}(n,t,sc) \cdot e - S_{out}(n,t,sc)] = 0$
(2.12)	Storage capacity limits $\forall\, n, t, sc$	$\sum^{T} S_{out}(n,t,sc) - \sum^{T-1} S_{in}(n,t,sc) \cdot e \leq 0\,;$ $\sum^{T} S_{in}(n,t,sc) \cdot e - \sum^{T-1} S_{out}(n,t,sc) - I_s(n) \leq 0$
(2.13)	Storage power limits $\forall\, n, t, sc, s$	$I_s(n) - S_{out}(n,t,sc) \geq 0\,;\, I_s(n) - S_{in}(n,t,sc)$
(2.14)	Non-negativity $\forall\, n, t, sc, s$	$G(n,t,sc,s) \geq 0\,;\, S_{out}(n,t,sc) \geq 0\,;\, S_{in}(n,t,sc) \geq 0$

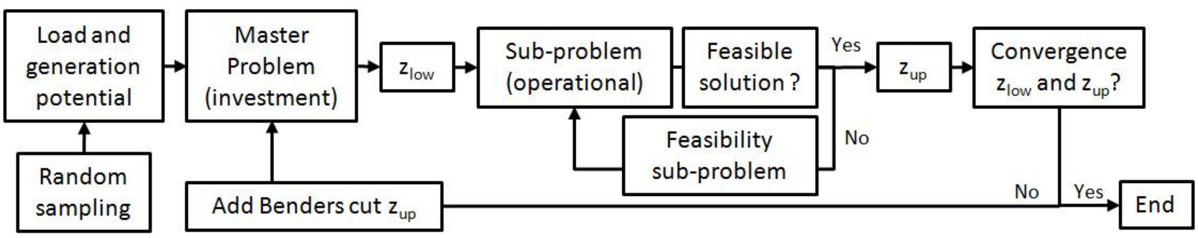

Figure 1: Algorithm used for solving the two-stage problem.

(Source: Own illustration)

The problem is formulated as two-stage stochastic optimization program, with initial investment at the first stage and operative optimizations at the second stage, see Figure 1. Benders Decomposition Method is applied with conflicting variables being initial investment levels into storage and DSM (Birge and Louveaux 1997). The first-stage (master) and the second-stage (recursive sub-problem) are successively solved in loops until convergence of the upper and lower level objective is reached. In this case, the sub-problem objective represents the upper bound as a restriction of the initial problem and the master problem yields a lower bound as a relaxation of the initial problem. The solution algorithm stops if the difference between the minimum upper bound and the current lower bound is less than or equal to a very small number; otherwise the algorithm continues. Benders optimality cuts are added to the problem set of constraints after each iteration. Moreover, feasibility cuts ensure that infeasibilities in the sub-problem due to misallocations in the master problem are ruled out, see Figure 1. The Benders approach reduces computation effort as compared to solving the extensive form expected-value-problem.

(2.15) Master Objective

$$\min_{I_s, I_d} \propto + \sum^{N} I_d(n) \cdot c_d + I_s(n) \cdot c_s$$

(2.16) Benders cut $\forall\, iter$

$$\alpha(iter-1) + \sum^{N} \big[\lambda_d(n) \cdot \big(I_d(n, iter) - I_d(n, iter-1)\big) + \lambda_s(n) \cdot \big(I_s(n, iter) - I_s(n, iter-1)\big)\big] \le \alpha(iter)$$

(2.17) Sub objective

$$\min_{\substack{G,D,\\ S_{in}, S_{out}, P}} \sum^{SC} prob(sc) \cdot \sum^{N} \sum^{T} \left[\sum^{S} c_g(s) \cdot G(n, t, sc, s) \right]$$

(2.18) Fixing variables to results of Master Problem $\forall\, n$

$$I_s = I_{s,MasterProblem}\ ; I_d = I_{d,MasterProblem}\ ;\ duals\ \lambda_d(n)\ and\ \lambda_s(n)$$

The relaxed master problem objective (15) includes α, the objective value of the sub-problem and is restricted by the Benders cut (16). The recursive sub-problem objective function is equation 17. Concerning the Benders cut, λ_d and λ_s correspond to the duals of the constraints (18) which fix the variables I_d and I_s to their values resulting from the corresponding master problem. α_{iter} is a decision variable setting the lower bound to the recourse problem after each iteration *iter*. Note that the iteration counter is added in the variable sets in equation 16 unlike all previous equations.

2.3 Application to a simple distribution system

This section describes the application of the presented model to a simple five-node 10kV medium-voltage-grid with characteristics representative for a typical distribution system structure in sub-urban Germany. Assumptions regarding the application are detailed hereafter.

2.3.1 Generation

Nine technologies are part of the generation mix in this application: Six technologies – hydro, nuclear, lignite, hard coal, gas and biomass – have generation capacities with full availability at any time (up to a technical factor, e.g. due to maintenance requirements, taken from EWI et al. (2010)). Three technologies have varying availability, with wind output being treated as stochastic parameter. Small-scale heat-controlled CHP diurnal patterns follow an approximation in Pudjianto et al. (2006) for both winter and summer and they are weighted by a seasonal factor to account for higher heating demand (and thus more electricity supply) during winter. Likewise, Photovoltaic power (PV) exposes different daily profiles by season adapted to a central German location (Jahnke 2012).

Available energy (per day, aggregated over all nodes)											
demand peak [kW]		1100									
Technology		**Wind**	**PV**	**CHP**	**Biomass**	**Hydro**	**Nuclear**	**Lignite**	**Coal**	**Gas**	Total
Type	Source	time-dependent	time-dependent	time-dependent	flexible	flexible	flexible	flexible	flexible	flexible	
installed capacity (Germany 2020) [GW]	EWI et al. (2010)	40.9	33.3	4	7.85	7.7	6.7	22.4	28.5	24.4	175.75
electricity generation (Germany 2020) [TWh]	EWI et al. (2010)	94	31	20	37	7.5	49.2	145.2	120.2	40.4	544.5
capacity utilization (where relevant)	Calculation		10.6%	57.1%							
technical availability (where relevant)	EWI et al. (2010)				88%	90%	93%	86%	84%	84%	
installed capacity [kW] (in model)	Calculation	537.44	437.57	52.56	103.15	101.18	88.04	294.34	374.50	320.63	2309.42
available energy, per day [kWh] (in model)	Calculation	varying	varying	varying	2178.57	2185.51	1965.07	6075.27	7549.94	6463.81	31638.31

Technology	**Wind**	**PV**	**CHP**	**Hydro**	**biomass**	**nuclear**	**lignite**	**coal**	**gas**
Marginal cost [EUR/MWh]	0	0	0	0	0	10	40	38	70

Table 2: Available capacity and projections of marginal generation cost incl. carbon cost in 2020.

(Source: Based on EWI et al. (2010))

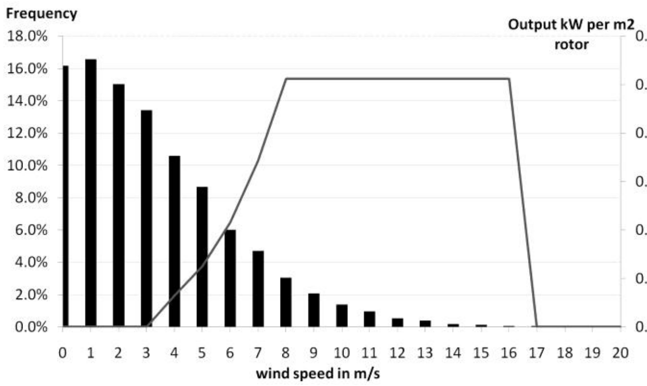

Figure 2: Frequency and power output under different wind speeds (average 5.22 m/s).

(*Source: Own production based on Roy et al. (2010)*)

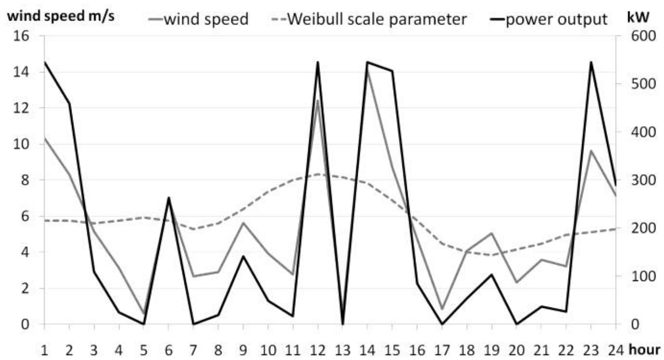

Figure 3: Simulated diurnal profiles of mean wind speed and output in winter (right).

(Source: Own production)

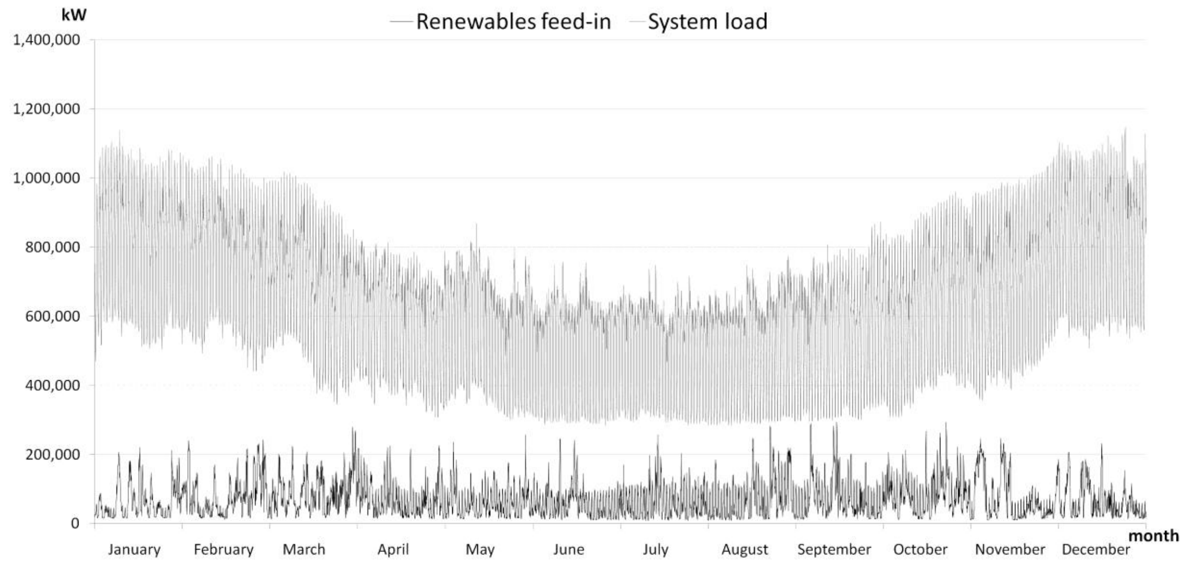

Figure 4: Feed-in and load of non-power-metered consumers in 2010 in NEW grid.

(Source: NEW Netz (2012))

It is assumed that generation capacities are distributed differently between the nodes of the small network – while the bulk of power will be available via the grid supply point, some of the CHP, PV and biomass capacity is located at the demand nodes. These assumptions are summarized in the parameters g_{max}, specifying the maximum available power from each generation technology per time slot and per node. Incremental generation cost is illustrated in Table 2. The figures are independent from the utilization rate of a generation technology.

Special attention is given to generation data of wind power which is treated as stochastic parameter. A Weibull probability distribution is used to create random samples of wind speeds just as in Roy et al. 2010). Equation 19 includes w, the wind speed, r, a random number uniformly distributed between 0 and 1, a scale and a shape parameter k and m. The shape parameter equals 2 (typical for Central Europe) and the scale parameter varies by time-of-day (Ekren et al. 2009; Roy et al. 2010; Giannoulis & Haralambopoulos 2011) and it is calibrated to match a typical on-shore location in the center of Germany.

(2.19) Inverse of the Weibull cumulative distribution function

$$w = -k \cdot [\ln(1-r)]^{\frac{1}{m}}$$

Knowing that energy potential per second (the power) varies in proportion to the cube of the wind speed (in m/s) it is then possible to calculate actual wind energy production in kWh. The number of wind rotors and their conversion efficiency are calibrated so as to match a share of wind energy in total production conform to projections in EWI et al. (2010). Cut-in, rated and cut-out wind speeds are indicated in Roy et al. (2010). To align with the size of the model grid the maximum wind power output is scaled down to 537.44 kW with 800 m^2 of installed rotor surface. The simulated random diurnal profiles (Figure 3) of wind output are validated against observed data in Giannoulis and Haralambopoulos, (2011), Niederrheinwerke (2011) (Figure 4) and simulations in Roy et al. (2010). The fact that wind speed is simulated as a Markov, non path-dependent, stochastic process may imply an over-valuation of investment into flexible storage and DSM.

Investment decisions into storage and DSM consider a long time frame and confront with uncertainty about the future generation technology mix. Whilst an investment appraisal should consider today's investment cost, generation cost reductions accrue in the uncertain future and should therefore be estimated accordingly. From the perspective of 2011, the year 2020 is a reasonable representative 'average' year regarding the penetration of RES over the life-time of a storage or DSM investment. Therefore, a hypothetical generation limit of each generation technology is derived from a forecast for the year 2020 given in EWI et al. (2010). The available installed capacity in Germany is scaled down. The share of installed capacity versus yearly peak demand in the model network corresponds to that of the national grid (EWI et al. 2010). Optimized generation profiles are outlined in the results section.

2.3.2 Demand

360 dwellings are assumed to be connected per 10kV-0.4kV transformer. Each consumer unit is equivalent to a 1.99-person household, a representative mix for Germany (EWI et al. 2010). The share of commerce and households is 21% and 79% in the model. The industrial sector is left out in the model because – by law - industrial consumers are already equipped with appliances for DSM when yearly consumption exceeds 100,000 kWh.

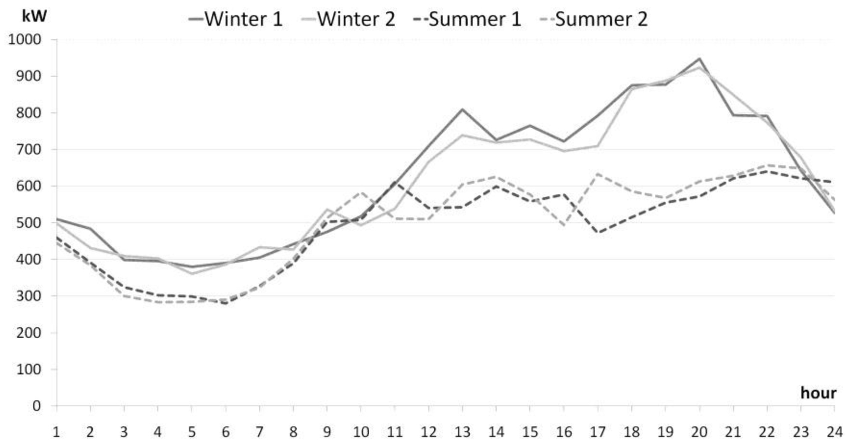

Figure 5: Sampled demand profiles in winter and summer.

(Source: Own production based on BDEW (2010))

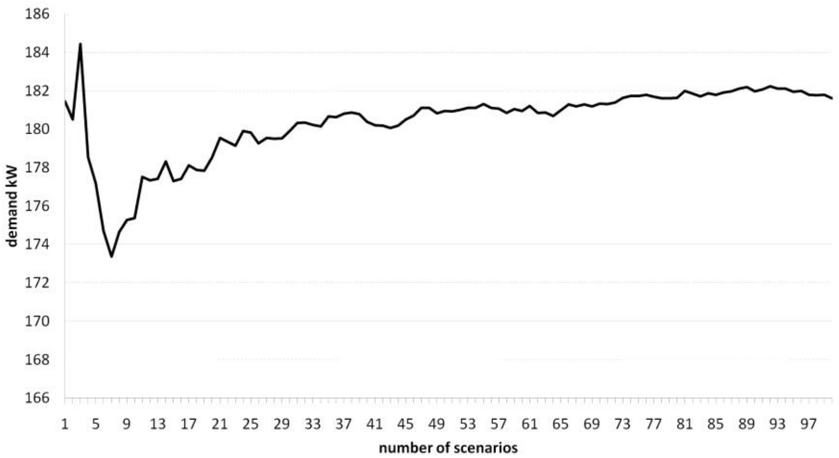

Figure 6: Convergence of sample demand mean with an increasing amount of scenarios.

(Source: Own production)

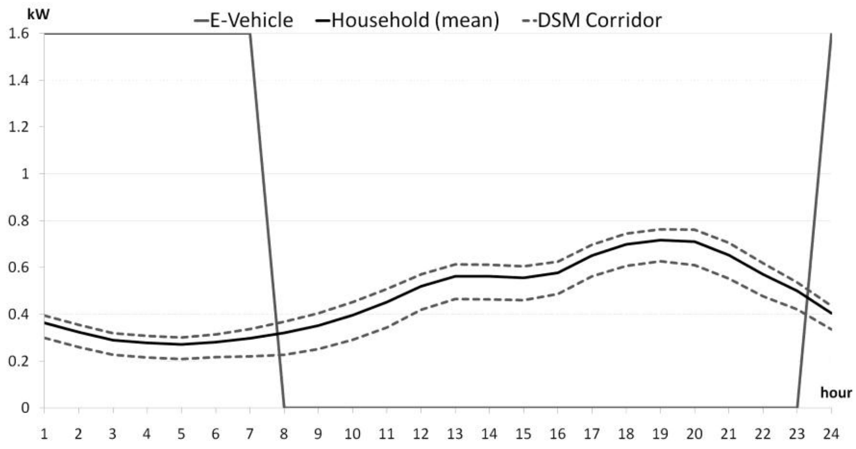

Figure 7: Deterministic mean standard load profile.

(*Sources: Own production based on BDEW (2010), Grein et al. (2009) and NEW Netz (2012)*)

A random sampling method is utilized for the simulation of demand realizations. Random sampling techniques are popular in risk analysis and used in research on electricity topics (Tan et al., 2010; Roy et al., 2010). Simulated stochastic demand values (Figure 5 and Figure 6) are drawn from a normal probability distribution with time-varying mean and standard deviation under the assumption of independence between wind power output and demand. The simulation creates 50 profiles which include the possibility of very extreme events. The mean values of demand realizations are taken from BDEW (2010) and averaged over months and types of day so as to create two single daily mean profiles per year with 24 hours each (summer/winter) as indicated in Figure 7. Standard deviations of demand variability are known to the optimizing agent based on empirical demand realizations at the EEX wholesale intraday market (EEX 2012). Deriving medium-voltage demand variability from wholesale market demand fluctuations is reasonable for model systems with aggregation of a high number of consumers. The more consumers are aggregated, the less volatile is energy consumption (Widen & Waeckelgard 2010). Fluctuating demand profiles outlined in Giannoulis and Haralambopoulos (2011) and Grein et al. (2009), projected profiles for 2020 in Moura and de Almeida (2010) and empirical data in Widen et al. (2009) and Niederrheinwerke (2011) were consulted for validation of the sampled demand profiles here. Maximum and minimum sampled demand in the modeled system figures at 1,100 kW and 240 kW, excluding EV. This is a spread of factor five and a deviation of 60-90 % around the average system demand (561 kW). Empirical data from 2010 in NEW Netz (2012) exposes a spread of factor 4 between peak and lowest demand. For an isolated island with 90,000 inhabitants, Giannoulis and Haralambopoulos (2011) show that the spectrum of demand values ranges 75-100% of the mean value either way while maximum and minimum yearly demand differ by factor eight. The spread of demand simulations in the model system here is thus comparable with empirical profiles at other distribution systems.

In this application electricity consumption of EV is incorporated into the stochastic reference demand q. A load pattern is assumed with 8 hours domestic charging time at a rate of 1.6 kW, referred to as Level 1 charging speed, see Figure 7. A full charge per night (12.8 kWh) would correspond to a 100 km range. Note that EV are not equivalent to storage facilities in the model. This implies no vehicle-to-grid technology is considered here. Uncontrolled EV solely behave as additional consumers whose load can be curtailed and shifted if DSM appliances are installed. Charging behavior is under full control of the system operator if the EV is connected to a smart meter. Different penetration rates of EV are tested from zero to 10%.

2.3.3 Load control

The DSM potential for average households and commerce is derived from a study report for the City of Mannheim, Germany (Grein et al. 2009) and triangulated with Stadler (2008). EV availability is added to the DSM potential. The resulting potential can be observed for each time slice in Figure 7 and Figure 12. Figure 7 plots an average load profile for a household with the corridor of maximum and minimum load when DSM appliances are installed. Positive and negative shifts are possible and their potential is asymmetric. The potential to increase energy load at each time, d_{pos}, is generally larger than d_{neg}.

The total cost of equipment for DSM figures in between 160 and 350 EUR per installed system EcoFys (2009). The application here refers to the so-called Advanced Metering System (AMM), which includes two-way communication via an integrated router gateway in each dwelling. This system enables time-of-use pricing and direct load control up to the capacities detailed in Figure 12. The cost figure includes investment into hardware such as meter, gateway, router and its initial installation. In order to calculate lifetime cost, a 6.5% annual discount rate is applied with a lifetime of 16 years (EcoFys 2009).

2.3.4 Storage

The model considers investment into a central large-scale stationary battery with endogenous capacity and conversion efficiency factor of 75%. The focus is on batteries instead of mechanical conversion systems (pumped hydro, compressed air storage) for batteries require little up-front installation cost. To account for different battery technologies, the cost input data is varied. Approximated cost data of equipment and installation is compiled in Table 3 for reference (Doughty et al. 2010; Electricity Storage Association 2011).

Conversion	Storage type	EUR/kWh	EUR/kW	Cycles (100%)	Efficiency
Mechanical	Supercapacitor	3,800-4,000	100-400	10,000-100,000	95-100 %
	Flywheels	1,000-3,000	300	20,000-60,000	90-95 %
	Pumped Hydro	60-150	500	20,000-50,000	70-85 %
	Compressed Air	30-120	550	9,000-20,000	70–80 %
Electro-chemical	Nickel-metal hydride	700-800	-	500-3,000	65 %
	Nickel-Cadmium	350-800	175	1,000-3,000	60-70 %
	Sodium-Sulfur	200-900	150	2,000-3,000	85-90 %
	Lithium-Ion	200-500	175	3,000-6,000	95-100 %
	Vanadium Redox-Flow	100-1,000	175	2,000-3,000	75-85 %
	Zinc-Bromine	50-400	175	> 2,000	70 %
	Lead Acid	50-300	175	200-1,100	75 %

Table 3: Storage investment cost data compiled from various sources.

Mechanical bulk storage included for reference but not considered in the calculations. (*Sources: EcoFys (2009), Doughty et al. (2010), Electricity Storage Association (2011)*)

In the cost considerations, a life-time of 3,000 cycles is assumed at 80% depth of discharge with one cycle being completed every three days, hence a life-time of 12 years. To facilitate tractability and increase computation speed, the three dimensioning vectors of a storage unit – capacity in kWh, charge rate and discharge rate in kW - are all set equal in this analysis. Such assumption is justifiable in a setting with hourly time resolution where ramping constraints and thus power limits are of secondary importance in contrast to capacity limits. In the real world, actual batteries often feature hourly power limits as high as energy capacity limits. This holds true notably for storage devices that serve as reserve for capacity markets.

2.3.5 Grid

A stylized configuration is simulated with characteristics that approximate realistic grids, as illustrated in Figure 8 (Fletcher & Strunz 2007; Niederrheinwerke 2011). The grid representation used in the case study here consists of five nodes, one of them the grid supply point (GSP) and additionally demand nodes with 10kV/400V transformers. The nodes are connected in line so as to simulate a 'worst-case' topology. The analysis restrains to the 10kV-level of a stylized distribution network. An application of the presented DC flow model to a 400V level is delicate for the DC load model does not include reactive power. At 400V level, voltage drop limits and reactive power are of high relevance. Large-scale generation, including wind turbines and pump storage, is assumed to be connected at the 10kV level, whilst DG and EV are part of the underlying 400V grid. 10kV overhead lines have a lateral surface of 70 mm^2 with associated capacity of 185 Ampere. In a 10kV DC setting this results in a maximum capacity limit of 1,850 kW. A typical reactance of the 10kV network is around 0.4 Ohm/km (Pudjianto et al. 2006; Fletcher & Strunz 2007). Upgrade costs of overhead circuits in a comparable 11 kV grid lie at 3,102 EUR/MW/km (Pudjianto et al. 2006). It is assumed all lines are 2 km long and line flows do not incur transmission losses. Grid reinforcements are not included as variable in the model equations delineated above but calculated ex-post in case grid capacity represents a shortage.

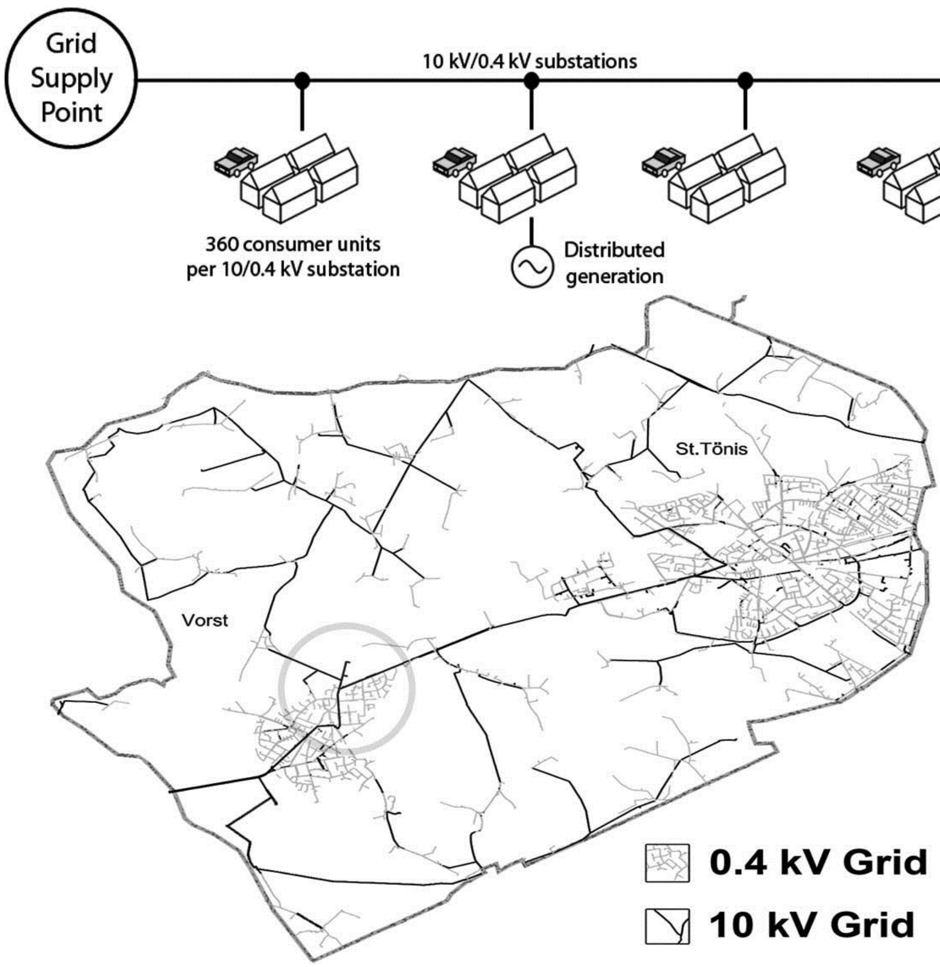

Figure 8: Stylized 5-node grid in a reference distribution grid.

(*Source: Own illustration and based on Niederrheinwerke (2011)*)

2.4 Results

The linear problem is implemented in GAMS, using the solver CPLEX 9.0 (GAMS 2011) with standard options. A 1.3 GHz CPU machine executes the stochastic linear program for one exemplary day in between 2 and 8 minutes time, depending on cost parameter values. Up to 20 iterations are needed. The deterministic model is solved within a few seconds time.

In Figure 9, optimal investment curves are interpolated from several mode runs. Storage devices are found to pay off at investment cost below 850 EUR/kWh of capacity. For instance, if costs amount to 300 EUR/kWh, storage devices are profitable up to a size of roughly 0.5 MWh capacity (and MW power limit) in the framework of the model, depending on the degree of EV penetration. That corresponds to about one fifth of installed generation capacity (2,309 kW) and one half of peak demand (1,100 MW) in the system. In total, it is found that less than 1% of aggregated electricity consumption is stored in most scenarios (Figure 10). Summed over all nodes, there are 309 kWh storage capacity (left graph) and 807 of the 1,440 consumers have DSM appliances installed (right graph). A higher number of EV, hence additional load, further improves the case for storage devices. Given these numbers, it can be concluded that even relatively expensive technologies such as Nickel-Cadmium and Nickel-metal hydride batteries seem to be profitable. In contrast, super-capacitors and flywheels need to severely cut their cost in order to become competitive. 2011 investment cost lies between 2,000 and 4,000 EUR/kWh.

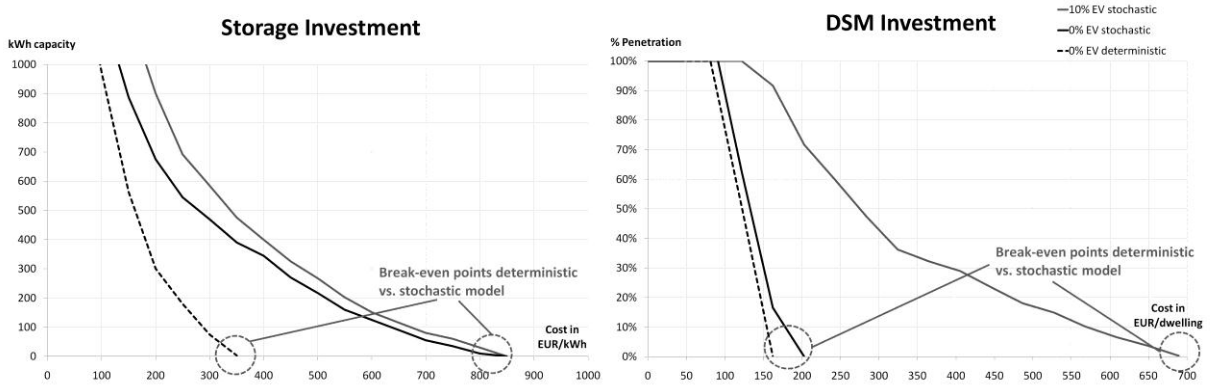

Figure 9: Investment into storage and DSM under varying investment cost and EV market penetration.

(Source: Own illustration)

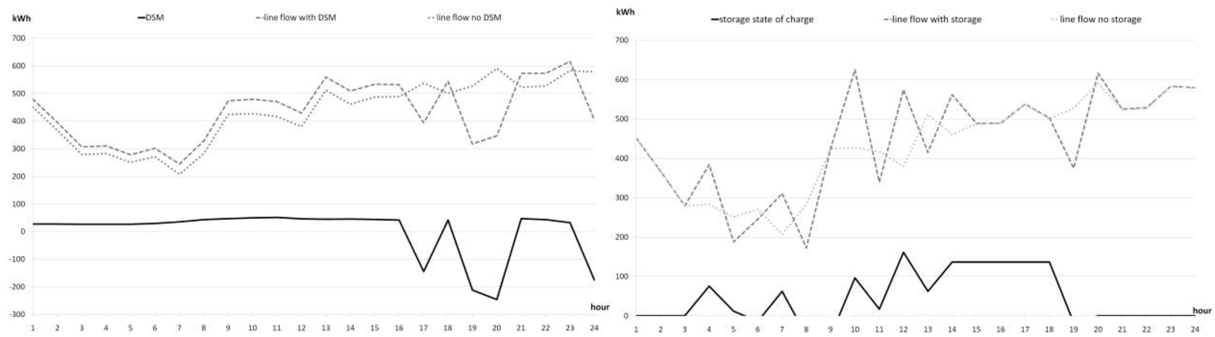

Figure 10: Storage operation, DSM operation and line flows in the course of a day in two scenarios.

(Source: Own illustration)

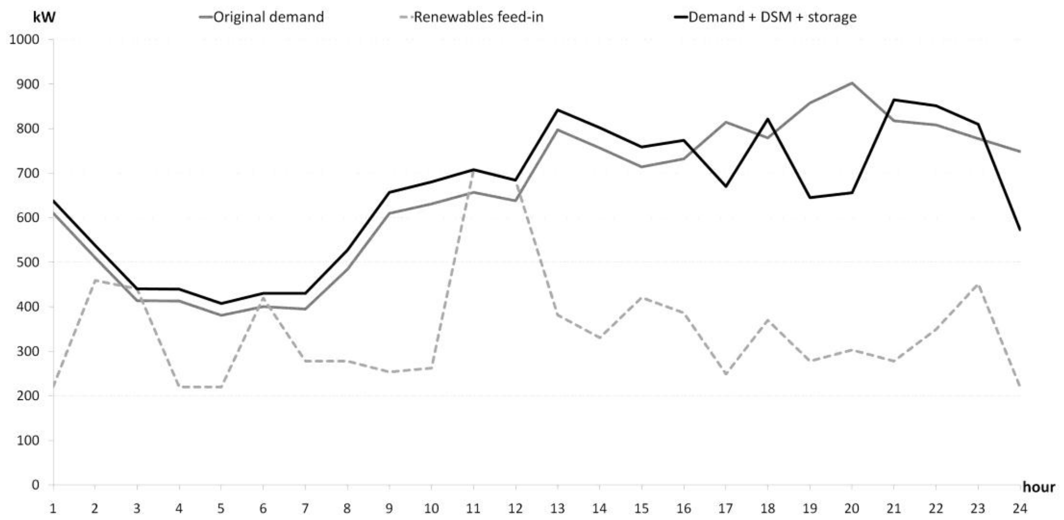

Figure 11: RES feed-in, original demand and load after storage and DSM shifts.

(Source: Own illustration)

Appliances for DSM prove hardly profitable in the deterministic model setting, which echoes a finding of Strbac (2008) and Electricity Journal (2008). Likewise, the stochastic model predicts DSM to be little beneficial in the absence of EV. Only if all-inclusive investment costs boil down to 200 EUR per consumer, investment into load control technology may become beneficial. Note that 2009 cost for AMM systems lies 260 EUR and projections for 2020 figure at a minimum of 160 EUR (EcoFys 2009). The break-even point (tolerance threshold) for investment into DSM increases up to 700 EUR when 10% of consumers own EV. Such strong shift clearly outlines that a high number of EV induces investment into load control equipment. When in competition to each other at current cost, investment into storage devices is thus clearly favored to DSM systems. This effect is minimal or partly reversed when EV penetration is high. Obviously, storage devices offer more flexibility to load management than does DSM.

The grid capacity is sufficient for a securely functioning system in all scenarios. Even with high penetration of EV, grid capacity constitutes no severe shortage since line flows do not exceed 60% of thermal capacity limits at any time slice and any scenario, as shown in Figure 10 (total limit 1850 kW). Moreover, alternative grid configurations such as a meshed grid would rather improve the situation. It can be concluded that no grid reinforcements are required at 10 kV level in the model setting. The grid representation constitutes a stylized grid with realistic characteristics so as to be able to generalize conclusions to a certain extent. While the stylized grid seems to be well equipped for additional future loads, this does not mean grid extensions are not needed at 400 V low-voltage level. In order to undertake studies at 400 V level, an AC network model would be appropriate. Such model would incorporate reactive power and voltage drops which are of high relevance in low-voltage grids.

At specific hours in summer, the system exposes an over-supply of RES feed-in. In these moments, DSM and storage operations are crucial. Figure 10 and Figure 11 illustrate how load profiles are adapted to better align with RES feed-in. Overall, the system predicts between 50 and 60% of demand to be covered by RES generation in the absence of storage and DSM, which is more optimistic than future projections for Germany in EWI et al. (2010) (34% RES generation by 2020). The use of storage and DSM slightly improves the coverage through RES. Figure 10 illustrates how line flows narrowly coincide with storage use indicating that line flows are to a great extent driven by storage operations. It is found that the introduction of storage devices enhances line flows at certain moments, see Figure 10. This implies a stronger capacity use rate than in the absence of storage, notably in peak periods, i.e. midday. All in all, grid system reliability is not affected by storage and DSM operation since line flows do not exceed a critical bound at any moment, neither with nor without storage and DSM.

A sensitivity study regarding the presence of EV in the year 2020 is illustrated in Figure 9. This is done to address the question of how EV modify the value of storage and load control. Obviously, a high number of vehicle charging augments demand and uncertainty and therefore strengthens the case for storage devices and DSM. If 10% of the consumers own and drive EV, investment into DSM appliances is likely to rise by more than 50% as compared to a world in absence of EV. All in all, results suggest that EV strongly induce investment into load control facilities. This result pretty much reflects the trivial fact that most EV are sold to home owners along with smart metering systems. A potential alternative to smart EV home charging solutions could have been to install central storage devices and let EV owners charge whenever they like (so-called dumb charging). However, the value of storage increases only slightly in the EV scenario. This result indicates that installing DSM appliances for EV owners to allow for smart charging is a much better solution than installing central storage.

2.5 Discussion

The application has shown a case where investment into storage is more profitable relative to DSM systems from an operator's point of view. Practical and management aspects strengthen the position of central stationary batteries for storage versus DSM systems. Central storage devices are much easier to handle than a high number of dispersed DSM systems. The latter also require decent communication systems for interaction between consumers and supply in order to be fully effective (Wissner 2011). Furthermore, storage offers a constant load potential at any time. When installing DSM systems, the availability of DSM potential is dependent on the consumer and it may temporarily be very low. Thus, storage devices offer more flexibility as compared to DSM systems. A drawback of storage is that it requires higher upfront investment cost and it may not go with consumption reductions in general. Consumption reductions can be reached through demand response programs and the offering of variable tariffs with the help of DSM systems. This latter effect (demand response) is left out in the analysis here. Furthermore, storage systems may be more vulnerable to fatigue and self-depletion and their lifetime might be shortened depending on the charging behavior.

What is the point of using a stochastic model? Results of the deterministic model indicate a tendency to under-invest as compared to the stochastic model's outcome. Figure 9 indicates that deterministic investment levels (dotted line) can be up to 50% lower than in the stochastic model (continuous lines) for storage. For both, storage and DSM, investment levels are consistently higher in the stochastic model. The value of the stochastic solution (VSS) is estimated to figure at around 0.5% to 5% of total system costs, indicating a gain in efficiency when using the stochastic model as opposed to the deterministic model. The VSS allows us to obtain the goodness of the expected solution value when the expected values are replaced by the random values for the input variables. It can be concluded that the cost of disregarding uncertainty lies at around 0.5% to 5% of total generation costs. On the other hand, the execution time of the stochastic model with a sample of 50 draws is roughly 15 times higher than the deterministic model. Computation times largely vary depending on the cost input data, though. All in all, the stochastic model is superior for it provides efficiency gains at reasonable additional CPU effort. The deterministic model appears to induce wrong long-term investment decisions and under-values the flexibility provided by storage and DSM.

The extensive form stochastic model solves in a slightly shorter time than the Benders decomposition model. If the model was extended so as to diminish stylization, the Benders model computation time should improve in comparison to the extensive form. This conjecture is supported by the fact that Benders decomposition is most suitable for outsized problems characterized by a capacious set of variables, nodes and parameters (Benders 1962). In these conditions it may be valuable to isolate a group of decision variables and investigate the problem partially with Benders method. The decomposition model presented here shall constitute a basis for further models of larger size.

2.6 Conclusions

The analysis here presents a DC load flow model applied to investment in storage and DSM facilities in a stylized medium-voltage grid. The model incorporates uncertainty in demand and wind output and uses Benders Decomposition to distinguish the investment choices from operative optimizations. It is shown how Benders Decomposition method can be meaningfully applied to a small-scale investment problem in a network-constrained industry.

The model is capable of reflecting multiple formats of short-term uncertainties in system constraints at the operational dispatch stage. Nevertheless, computation time reductions were not achieved in the small model application presented here.

The model results indicate that grid reinforcements at 10 kV level are not necessary in any of the scenarios. Capacity utilization rates do not hit the 60% bound, which implies there is little harm to system stability in the presented application.

Results in this application suggest that storage devices are beneficial at capacity cost of up to 850 EUR/kWh under the stipulated conditions. This implies that relatively expensive storage technologies such as Nickel-Cadmium and Nickel-metal hydride storage are profitable at current cost. Flywheels and large-scale capacitors are not competitive unless cost is reduced to 25% of 2011 cost.

DSM is not beneficial in any scenario, particularly in the deterministic model. Investment is beneficial up to an all-inclusive cost of roughly 200 EUR per consumer. This break-even point (tolerance threshold) boosts when consumers own EV, implying that EV strongly encourage investment into load control systems. The finding reflects the actual fact that most EV are sold along with advanced ('smart') metering systems.

As a logical consequence, it is found that investment into storage is likely to crowd out investment into DSM appliances in the model setting. Since both options are direct alternatives for energy management, 'smart meters' seem to be of little economic value to the system operator in the absence of EV. Unless governments strongly encourage DSM through obligations (beyond current obligations) and financial incentives or the promotion of EV, storage facilities are the better option for a vertically integrated distribution system operator facing the conditions of this model. The present analysis aimed at modeling conditions that would be representative for a section of a stylized distribution system in Germany.

It was shown, that the stochastic model produces more efficient solutions than its deterministic counterpart. The cost of disregarding uncertainty lies at 0.5-5% of total generation cost. The analysis demonstrates that a stochastic treatment of wind and demand patterns significantly augments the case for the use of storage. The break-even point for investment decisions into storage increases from 350 to 850 EUR/kWh when uncertainty of wind and demand are taken into account. Hence, the deterministic model leads to considerable under-investment into storage.

All in all, the results are highly sensitive to the assumed investment cost for storage and load management devices. EV are another cause for variations, yet, to a lesser extent. The calculations indicate that the value of storage strongly varies with the intermittency of wind output. The value of DSM is less sensitive to wind but more sensitive to EV penetration.

There are a number of conceptual caveats to the analysis which constitute areas for improvement. Energy saving through demand response is entirely factored out. The model may therefore underestimate the value of DSM to a minor extent. Furthermore, the investment cost for batteries is calculated on a diurnal basis with a fixed number of cycles per day. Fixing the cycles is a necessary step to obtain an exogenous cost figure but somewhat arguable since the cycles are endogenously determined in the model. Another drawback of this model is that some potential business cases of batteries and DSM are not included. Besides peak load reductions and network reinforcement deferral, Wade et al. (2010) point to other benefits of using storage devices. For instance, balancing markets as potential business field for batteries are not included in the present model. Other shortcomings are the stylized grid configuration, the missing reactive power in the DC load flow model and the absence of ramping constraints for storage. An application to a grid of larger size is an option for subsequent research.

2.7 Appendix

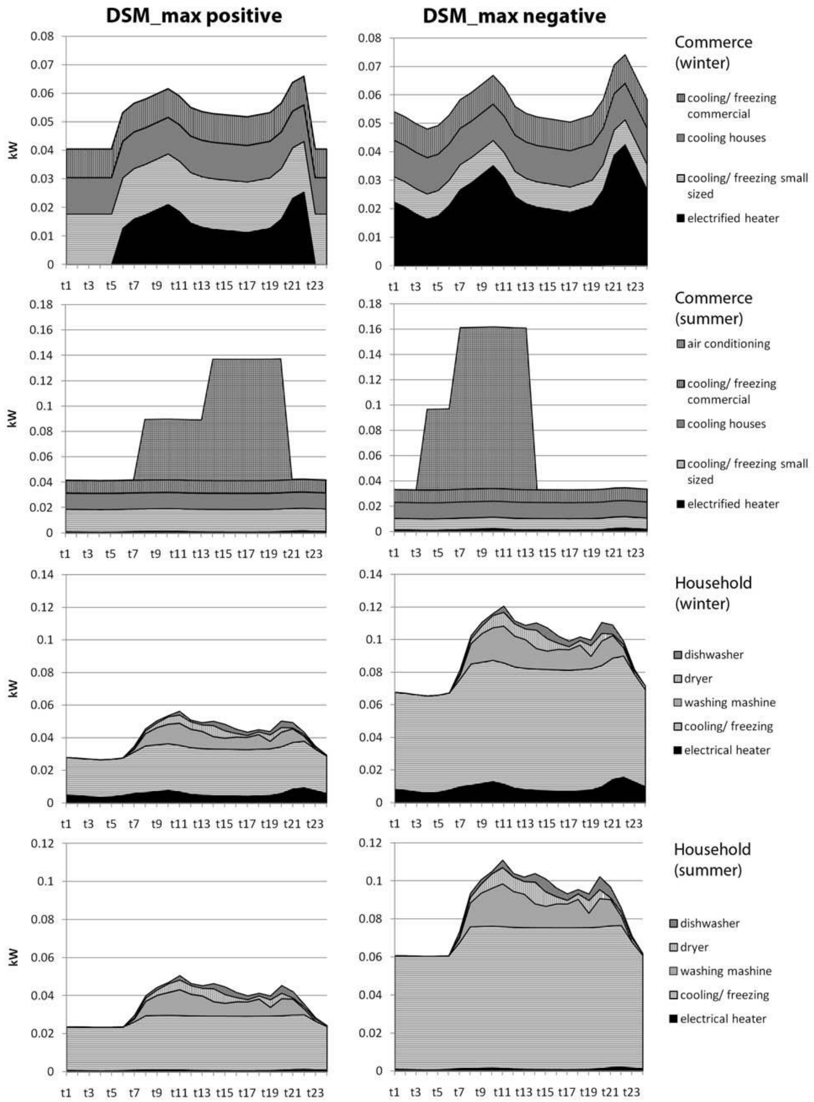

Figure 12: d_{neg} and d_{pos} for households and commercial units in kW during a day. EV profiles excluded.

(*Source: Own production based on Grein et al. (2009) and Widén et al. (2009)*)

Nomenclature

Set	
n	node with subset *nn* (1-5)
l	line (1-4)
t	hour (1-24)
s	technology (wind,solar,PV,CHP,biomass,hydro,nuclear,hardcoal,lignite,gas)
sc	scenario (1-50)
$iter$	iteration (unlimited)
Variable	
$D(n,t,sc)$	demand shifting (kWh)
$S_{in}(n,t,sc)$	storage inflow (kWh)
$S_{out}(n,t,sc)$	storage outflow (kWh)
$G(n,t,sc,s)$	generation (kWh)
$I_s(n)$	investment in storage (both kW and kWh)
$I_d(n)$	investment in a DSM system (absolute number)
$P(l,t,sc)$	phases angle difference (-)
Parameter	
$q(n,t,sc)$	consumer demand (kWh)
$g_{max}(n,t,sc,s)$	maximum generation capacity (kWh)
$c_g(s)$	variable generation cost (EUR/kWh)
c_s	levelized investment cost for storage (EUR/kWh and EUR/kW)
c_d	levelized investment cost for DSM (EUR/kWh)
e	storage efficiency (%)
$d_{pos}(t,n)$	positive load shift capacity (kW)
$d_{neg}(t,n)$	negative load shift capacity (kW)
$lf(l,t,sc)$	electricity flow (kW)
$x(l)$	line reactance (Ohm)
$b(n,n)$	network susceptance matrix (-)
$h(l,n)$	weighted network matrix (-)
$lm(l,n)$	incidence matrix (-)
$lf_{max}(l)$	maximal capacity for line flow (kW)
$slack(n)$	slack variable (-)
$p(sc)$	probability (%)
λ_s	dual of fixing storage investment in subproblem (EUR/kWh and EUR/kW)
λ_d	dual of fixing DSM investment in subproblem (EUR per dwelling)
$\alpha(iter)$	sub-problem objective (EUR)
$I_{sMasterProblem}(n)$	investment in storage from master problem (both kW and kWh)
$I_{dMasterProblem}(n)$	investment in a DSM system from master problem (absolute number)
w	wind speed (meter/second)
k	Weibull scale parameter (-)
m	Weibull shape parameter (-)
r	random number with uniform distribution (0-1)

Chapter 3 – Fast Charging Infrastructure for Electric Vehicles

3.1 Introduction & Literature Review

It is currently uncertain which charging technology for battery-powered EV will become the de facto market standard. Besides home charging, the most prominent and most debated solutions are fast-charging stations and battery-exchange stations. Whilst the necessity of home-charging solutions is undoubted, little is known about the usefulness and economic rationale of public fast chargers. The present chapter aims at providing an insight into the economics of this technology, which is hitherto little explored research-wise but is widely debated by the public. Public fast-chargers have the benefit of facilitating long-range drives for EV, and thus could serve as a means to mitigate range anxiety, with EV users having the opportunity to access public charging infrastructure at times when they are running low on charge. This factor may be crucial to increase market penetration of EV. Fast charging attracts EV users for it replicates the ease of conventional refueling and it attracts potential operators for it appears as being the only type of charging station to potentially promise reasonable returns. However, the technology has significant disadvantages as it may negatively affect battery lifetime, electricity system reliability and RES grid integration. For this reason, several stakeholders support night charging with smart grid applications, while others call for fast-charging solutions stressing its crucial role as range-extender.

There is relatively little research addressing with EV charging infrastructure, particularly when it comes to fast chargers. Åhman (2006) reviews public efforts to support EV deployment in Japan, including charging infrastructure. Likewise, Skerlos and Winebrake (2010) describe public policies in the United States that address EV, including charging infrastructure. Brown et al. (2010) delve into EV standards used in the United States where the infrastructure constitutes an important part of standardization. Nansai et al. (2001) conduct a life-cycle analysis of charging infrastructure at different public locations in Southern California with strong focus on environmental effects.

In general, a great deal of literature addresses optimized home charging, which is only a secondary focus of this chapter. Some research papers also include charging profiles of public EV stations. Kang and Recker (2009) conduct an activity-based assessment of EV energy impact and thereby use 1 year travel data to derive a typical charging profile of a public charging station amongst other findings. Other charging profiles can be found in Markel et al. (2009), who analyze fuel displacement potentials of EV under various use rates of public (fast) charging stations. Cost data for fast charging infrastructure can hardly be found in the peer-reviewed literature but is exposed in project studies (Wiederer & Philip 2010; Morrow et al. 2008; Slater et al. 2009; Wietschel et al. 2009; PlanNYC 2010).

The present analysis aims at shedding light on the economics of public fast-charging for EV. An economic valuation that should provide insight in the investment decision for a single fast charging station by estimating contribution margins is presented. The following research questions are addressed: At which use rate do level 3 charging investments pay off? Which markup would be needed? What would be the value of an on-site storage device to complement the charging system? Results are ought to serve as a basis for an application of a real options approach to EV charging infrastructure valuation in subsequent research work.

The article is divided into five sections. The introduction is followed by the model presentation. Subsequently, contribution margins, which arise through the daily operation of a charging station, are calculated. In this section, it is investigated how on-site storage can improve the economics of charging stations. We close with a conclusion.

3.2 Input parameters

Figure 13 illustrates the composition of cost and revenues from the operation of an EV charging station. The key drivers of turnover are the tariff (markup), power limit and utilization rates, which in turn are estimated based on assumptions on EV charging and driving behavior.

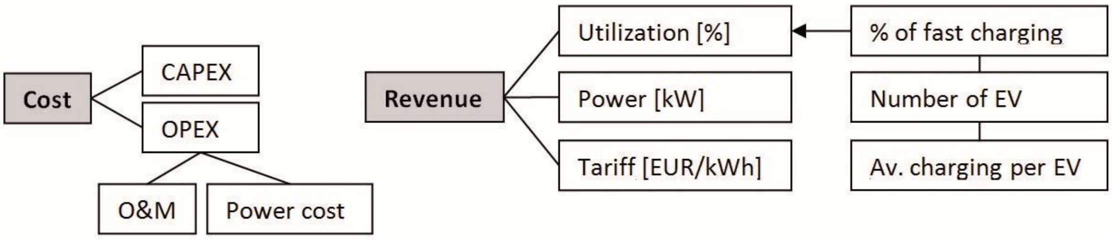

Figure 13: Parameters affecting cost and revenue stream.

(Source: Own illustration)[9]

3.2.1 Investment cost

Investment cost is compiled for different charging station types in Table 4. Generally, the industry distinguishes three charging levels. The range extends from level 1 chargers (low-speed) which are commonly used for home-charging to level 3 chargers (high-speed). Due to cost and thermal limits it is most efficient to deliver high-voltage electricity in direct current (DC) directly to the vehicle's battery pack. Such high voltage and high-current charging is called a DC Fast Charge (level 3) in contrast to less powerful AC charging levels 1 & 2 and 3-phase AC charge (level 3). CHAdeMO is the first international standard for public Level 3 DC charging solutions. It originates in the Japanese market, is penetrating the United States and may enter Europe. A large-scale fast charging station network has not been implemented in Germany until 2010 and it is uncertain whether CHAdeMO or 3-phase AC power will become the de facto standard for possible applications.

The cost figures compiled in Table 4 include carefully selected numbers. Since the various sources suggest all different cost figures, the numbers given in Table 4 are merely educated guesses, discussed with industry experts. The aim is to provide the model with thorough parameters without any claim for exactness. Total cost of installation varies greatly depending on the necessity for upstream grid reinforcement. Level 1 and 2 chargers usually require little grid upgrade. The high power involved in Level 3 charging is beyond the capacity of most utility transformers serving residential areas. Grid and transformer upgrades may therefore be required. Additionally, maintenance of on-street charging furniture may also be significant. As a rule of thumb, annual maintenance and repair figures at 10% of investment cost according to industry experts. The life-length of a charging spot is estimated at 10-15 years for level 3 chargers (Wiederer & Philip 2010).

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[9] O&M = Operation and Maintenance

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	Level 3 DC public	**Level 3 AC public**	**Level 2 public**	**Level 1 public**
Station lifetime (years)	10-15	10-15	20	20
Load limit (Volt)	500	400 (3 phase)	230 (1 phase)	230 (1 phase)
Load limit (Ampere)	125	96 (3·32)	32	16
Current	DC	AC	AC	AC
Power limit (kW)	62.5	50	7.3	3.6
Av. duration of 20 kWh charge cycle (min)	19	24	164 (2.74 h)	333 (5.6 h)
Max. number of 20 kWh charging EV/day	75	60	8	4
Calculation of 3-phase power: $P = U \cdot I \cdot \sqrt{3} \cdot \cos(\varphi)$ with $cos(\varphi) = 0.7515$ as a standard value used here.				
Material cost (EUR)	40,000 (40,000 – 75,000)	40,000 (40,000 – 75,000)	2,000 (2,000 – 7,500)	1,500
Grid reinforcement cost/civils (EUR)	14,000	14,000	1,000	500
Transformer cost if applicable (EUR)	0 - 35,000	0	0	0
Total CAPEX (EUR)	54,000	54,000	3,000	2,000
Maintenance and repair (EUR/ year) Rule-of-thumb: 10% of material cost	4,000	4,000	200	150
Total OPEX (EUR)	40,000	40,000	4,000	3,000
Life-cycle investment cost (EUR)	94,000	94,000	7,000	5,000

Table 4: Compilation of information on EV charging station cost.

(Source: Comparison of diverse sources, i.e. Morrow et al., 2008; Slater et al., 2009; Wietschel et al., 2009; Wiederer and Philip, 2010)

All in all, the cost difference between public level 1 and 2 versus public level 3 chargers seems flagrant at first glance. Aggregating over all users, though, fast charging infrastructure is equally expensive with ca. 1,250 EUR per EV. Note, that a single fast charging station can serve up to 75 users per day, while a level 1 charger is designed for a maximum of 4 users per day. Hence, almost 20 slow chargers would be needed to equal one fast charging station. Furthermore, all EV need to be equipped with costly and weightily AC/DC converters, which are not necessary if batteries are replenished solely through DC fast charging. Hence, if the entire battery charging system for EV would rely on DC fast charging only, EV owners could save the cost and weight of additional converters.

The cost of installed recharging posts in Table 4 does not count the expenses required to plan the deployment and to acquire planning permission. Nor is rental cost for parking spaces included. This decision is mainly driven by the largely varying cost per space we expect to see across regions and cities. Furthermore, parking availability is to be a primary concern for fast charging stations as opposed to level 1 on-street chargers.

Regarding on-site storage adjoined to the charging station, it is assumed that the storage device has 30 kWh capacity and 30 kW power limit, 85% conversion efficiency rate at total cost of 6,000 EUR (200 EUR/kW). This can be considered as relatively low-cost device with standard conversion efficiency.

For the calculations of contribution margins, one must distinguish life-cycle cost and levelized investment cost. While life-cycle cost refers to total CAPEX, yearly levelized investment cost distributes total cost over all years and is calculated as follows, with *i* being the interest rate and *n* the lifetime of the project.

(3.1) $\frac{CAPEX}{year} = CAPEX \cdot annuity\ factor$

(3.2) $annuity\ factor = \frac{(1+i)^n \cdot i}{(1+i)^n - 1}$

With interest fixed at 4% and a life length of 10 years, we obtain an annuity factor of 0.1233, which implies a yearly CAPEX of 12.33 % of total CAPEX. A fast charging post with total CAPEX of 94,000 EUR would thus require a levelized yearly CAPEX of 11,589 EUR. If a storage device of 30 kWh capacity is added at cost of 200 EUR/kWh, the total CAPEX amounts to 100,000 EUR which translates into levelized CAPEX of 12,233 EUR/year. To that figure, one needs to add annual OPEX to obtain total cost.

3.2.2 General demand for fast charging

Since the average vehicle is parked 95% of the time and most of its trips are short (Kempton & Tomić 2005), it is likely that EV owners will mostly rely on home charging solutions. On the other hand it can be argued that EV will only spread widely if a critical number of public charging facilities exist, including fast charging infrastructure.

When it comes to comparing the cost of fast charging infrastructure versus home charging solutions, there is a clear advantage for home charging. Boxes in garages cost less than 500 EUR, are easy to be installed, little vulnerable to vandalism and no grid reinforcement is needed. Furthermore, home charging promises to be a good option for controlled charging operation with RES integration as a primary target. However, national statistics from household travel surveys in Germany and the United Kingdom indicate that ca. 70% of car owners do own of-street parking facilities in suburban areas. This percentage drops to below 30% in metropolitan centers, hence areas where EV are set to spread at the outset. In the United States, Coloumb Technologies estimates there are 54 million garages for ca. 250 million registered cars meaning that a vast majority of cars would need to rely on open charging facilities. Taking into account hybrid EV and expressed in terms of trips, Kang and Recker (2009) estimate that 70–80% of all Hybrid EV trips (with 97 km range) can be powered by home charging. Consequently, a widespread and comprehensive spread of EV requires public charging options. While a system relying on home charging can serve up to 70-80% of household transportation demand, a comprehensive fast charging system would be able to cover almost 100% of that demand segment.

In this line, estimations given in Wietschel et al. (2009) imply that roughly 20% of all EV car owners would require fast charging solutions if all cars were EV; cf. Figure 14. Hence, if 1% of the whole car fleet in a specific region consists of EV, it should be reasonable to assume that at least 0.2% of all cars at a gas station with EV charging post are EV. Knowing that a high-volume highway gas station serves approximately 500-1,500 cars in average per day (Barnes & Liss 2008), 0.2% translates to an absolute number of one to two cars per day. The rough estimate is based on the assumption that driving patterns and fuelling customs will remain unmodified for EV owners when compared to conventional drivers. However, EV must re-fuel more frequently than conventional cars. We believe the factor of EV charging frequency versus conventional car fueling to be at two, since the range of conventional cars is about double the size of EV. Therefore, a general EV adoption rate of 1% could also lead to an average demand of 2-6 EV/day. All in all, these considerations show how uncertain demand estimations are. For this reason, we revert to a scenario analysis with different demand volumes.

A single CHAdeMO charging spot of 62.5 kW power limit can serve a maximum of 75 EV slots per day, cf. Table 4. As we consider ca. 50% to be a reasonable maximum tolerable occupation rate of a station we limit the scenario analysis to between zero and 40 cars per day [0-800 kWh/day]. When EV adoption rates are higher, a filling station should ideally be equipped with more than one single fast charging spot in order to avoid unnecessary queuing of EV users.

Naturally, the degree of competition and the geographical location of a station matters for demand. However, such particulars are left aside in this analysis, but the situation of a stylized typical station type is assessed. Note that we exclude hybrid EV, rollers and other non-car EV as we believe these segments to be marginally relevant for the economics of public fast charging solutions.

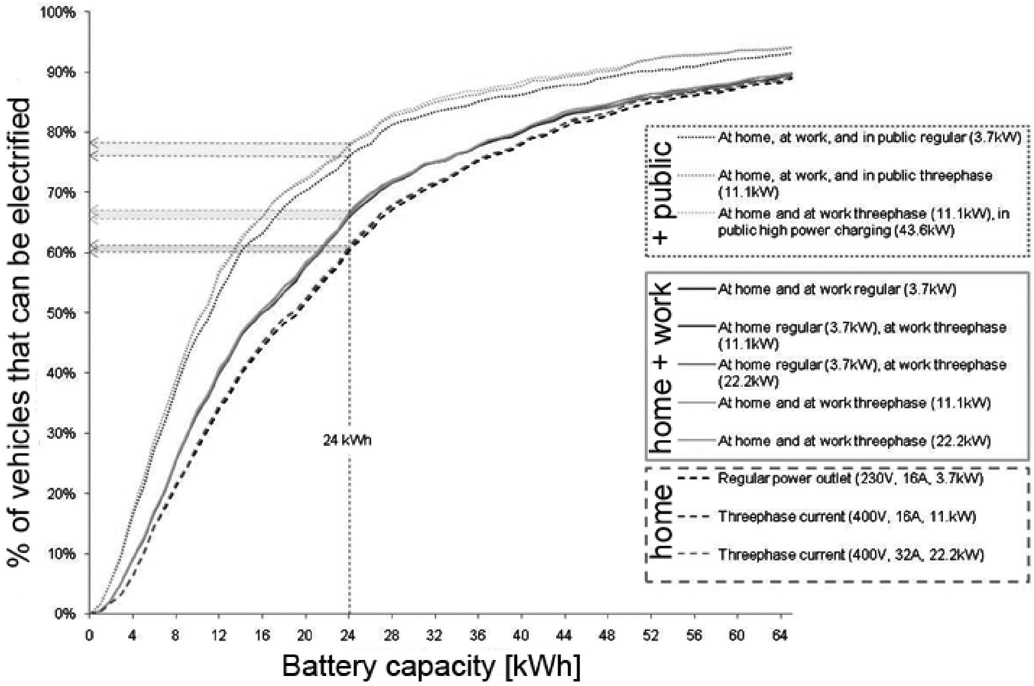

Figure 14: How many EV can be fed through which charging infrastructure?

(Source: Wietschel et al., 2008)

3.2.3 Use pattern

The shape and amplitude of the demand profile strongly influences the profitability of an EV charging station. Therefore, total demand and the pattern of daily electricity dispatch is a critical consideration in estimating the business case. Refueling patterns can vary considerably across geographical sites and across the type of customers served. As discussed in Barnes and Liss (2008), there are three common fueling patterns which can be cited as (i) random – vehicles come to refuel as needed; (ii) regular – vehicles refuel according to a predictable pattern; and (iii) constant – vehicles pool together at a set time and refuel one after another. We believe the random fueling type to be the most likely pattern for public EV fast chargers. However, demand is likely to have a predictable (though unplanned) pattern. To assist in formulating a demand profile, data were gathered and analyzed from key information sources, including Kang and Recker (2009) and Barnes and Liss (2008).

Barnes and Liss (2008) shows that normalized profiles are relatively stable irrespective of the fuel station location and type (Hydrogen, Natural gas, gasoline). The main difference between different types of stations is not the profile but the amount of fuel demand that can be observed with demand at residential stations being roughly double the size of demand at interstate stations, according to data presented in Barnes and Liss (2008). Bearing this in mind, we proceed with the calculation of a stylized charging pattern that could possibly be observed at an EV fast charging station independent of its exact geographical location.

The hourly demand data from Conoco Phillips gasoline fuel stations stipulated in Barnes and Liss (2008) were used to develop electricity demand values for a 62.5 kW EV charging station over a period of one average week. Such derivation can be made under the assumption that demand for fast charging will have similar characteristics as conventional gasoline demand in terms of its temporal profile. As the defined aim of fast charging solutions is to make electricity charging as much as possible like conventional fuel dispensing, the assumption should be reasonable. EV recharging ought to replicate the convenience of refuelling with gasoline.

A rounded estimate of the number of vehicles filled per hour over the course of a week is outlined in Figure 15, where the dashed line illustrates deterministic values. With the stipulated assumptions, the average demand per day is 20 EV per day and the average demand per EV is a 20 kWh charge. The input values were subsequently varied, as presented in the results section. We assume 20 kWh as an average charge because fast charging stations are likely to attract users inclined to long-distance travel. It is indicated in the beginning of this chapter that fast chargers have a key function as range extender for long-distance travel. It would therefore not be sufficient to take the average charging of all EV and hybrid EV per day (10-20 kWh) as a function of distance driven in average per day (32 miles (51 km) in the United States, according to Kempton and Tomić (2005). The demand per charging cycle is probably much higher for public EV fast charging stations than for conventional level 1 and 2 chargers. We believe that an average charge of 20 kWh would be more likely to occur in reality. With a 20 kWh charge and a consumption of 10-15 kWh/100km, an EV driver can travel a distance of roughly 125-200 km. 20 Minutes is needed to replenish batteries at a CHAdeMO-standard 62.5 kW post. That would represent a ca. 80% charge of a Nissan Leaf battery (24 kWh) and little more than MiEV battery capacity (16 kWh). 20 kWh would correspond to a ca. 40% charge of a Tesla Roadster battery (53 kWh) or a ca. 20% charge of a BYDe6 battery (72 kWh). These two EV are specifically designed to make long-range EV trips possible.

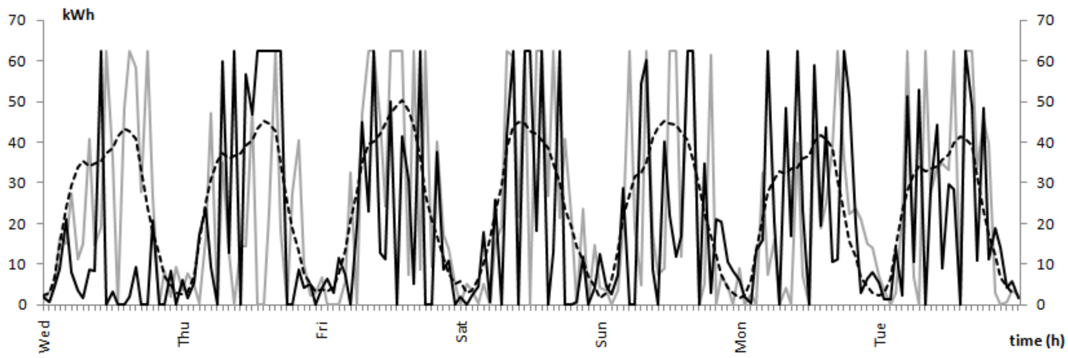

Figure 15: Two synthetic weekly EV demand profiles at 62.5 kW station with 30 EV/day (600 kWh).

(Source: Own illustration)

Figure 15 clearly sketches how randomly sampled profiles add to the volatility of mean demand profiles. In real life, charging station operators are likely to be confronted with a highly volatile load demand, which turns out to be much less at their convenience than `smooth` mean values. Simulated charging demand follows a normal probability distribution with time-varying mean Barnes and Liss (2008) and an arbitrarily chosen standard deviation of one third of the mean. Since no real world charging data from fast charging stations is publicly available, it is necessary to approximate a standard deviation that yields realistic samples. All in all, the charging profile is moderately sensitive to the choice of a standard deviation. Details of the calculation of electricity demand can be found in Appendix.

The randomly sampled profile excludes negative demand values and demand values exceeding the capacity of a single charging station of 62.5kW. All realizations outside the interval [0; 62.5] were cut out. In a transferred meaning, if demand is beyond 62.5 kWh some EV either wait or find alternative charging spots. Eventually, demand is varied as exogenous factor in a scenario analysis. Figure 15 plots the remaining values of a weekly demand profile with average demand of 20 EV/day. These represent two randomly sampled charging profiles in the course of a week. All profiles follow an obvious pattern of peak demand during day-time and low demand during the night. Mean values feature a consistent pattern for mid-week fueling, with a slight peak early in the morning followed by the highest level of demand around 5 pm. Peak demand occurs on Fridays.

3.2.4 Electricity prices and tariffs

The charging operator is assumed to have perfect foresight of electricity purchase prices from the energy exchange. This assumption is reasonable in a setting with hourly time resolution. The price spreads and hours with lowest and highest prices are, in general, fairly predictable while other factors, such as charging profiles, are a greater source of volatility than electricity prices in the course of a day, cf. Figure 15. The simplification can potentially imply an overestimation of the true arbitrage value of a storage device. However, Sioshansi et al. (2008) prove how operation strategies with perfect foresight of hourly spot prices can capture 85-90% of the potential arbitrage value of a storage device. Although literature finds that storage devices are in general too expensive to pay off simply by their arbitrage value, the setting of an EV charging station may reveal to be slightly different since tariff mark-ups allow for a greater arbitrage range.

Figure 16 plots the tariffs used in the calculations. Two different types of tariffs are investigated: (a) a flat rate; and (b) a time-of-use rate (TOU). The willingness of the customer to pay a markup or a subscription fee is untested so far. Accordingly, we retrieve to sensitivity analysis regarding the allowed markup rate as exogenous model input factor. Naturally, the markup is considered as margin over total electricity cost, including taxes and fees. Hence, the electricity cost profile plotted in Figure 16 includes not only sport market prices from German EEX (2010) but also other cost components such as fees and taxes representative for Germany. Expressed in ct/kW, these comprise electricity tax (2.1), grid fees (0.5), grid concession (0.3), measuring cost (6.0), distribution (1.99), RES and combined heat and power allocation (0.8) and a variable purchase tax (19% of EEX price). Values were gathered from the German Wind Energy Association.

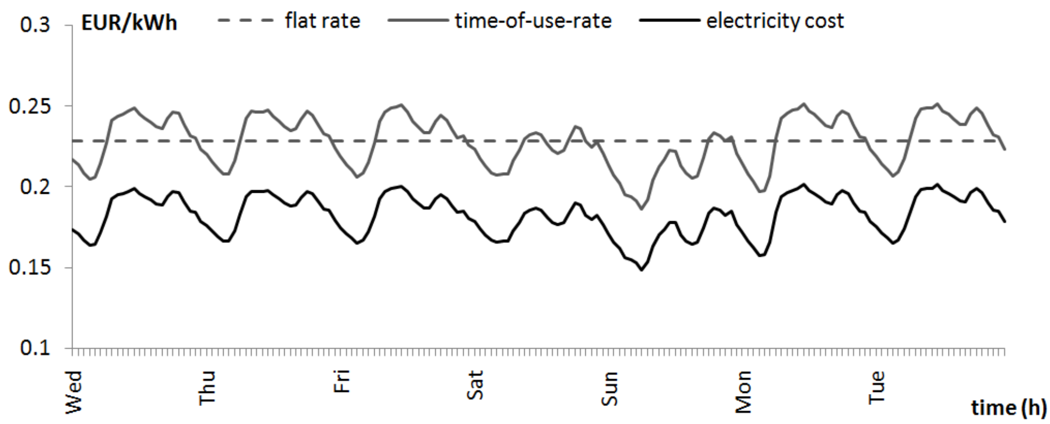

Figure 16: Exemplary retail tariffs and electricity cost profile used in the calculations.

(Source: Based on EEX (2010))

3.3 Method

In this section, we present the procedure for a valuation of a CHAdeMO-conform 62.5 kW charging station operation by an independent agent who purchases electricity at wholesale prices. The economic valuation proceeds in three steps: First, a finite number of charging stations is defined a priori. We set this number to one. Second, a random sample of 50 different demand profiles (Figure 15) is created and operational arbitrage profits are identified under various tariffs (Figure 16). In Figure 16, an average markup of 25% is assumed and electricity cost includes average EEX spot market prices for 2010 plus taxes, fees and all other costs. Subsequently, an ex-post optimal hourly strategy of an on-storage device is optimized to check how storage improves profits (equations below). In a third step, the annual net profit of the charging station is compared to its levelized investment cost so as to obtain a Return on Investment (ROI) figure as indicator of profitability. ROI is expressed as a percentage value.

(3.3) $$ROI = \left(\frac{Annual\ Net\ Profit}{Levelized\ investment\ cost} - 1\right) \cdot 100$$

ROI represents a short-term assessment that indicates what operating contribution margin a charging station can achieve under various conditions. The advantage of the ROI concept over long-term evaluations such as NPV and real option evaluation is that it does not require any assumptions on the uncertain dynamics of costs and prices in the far future.

The operation of an on-site storage device of 30kWh capacity is simulated with the linear optimization program outlined below. The operator's objective (equ.3.2) is to maximize the yearly profit from charging station operations through appropriate on-site storage management under a given tariff. He must serve demand, there is no curtailment of demand. *SOUT* and *SIN* are positive decision variables. Q_{ref} is load demanded, p_{ref} is the electricity wholesale price and *prob* is the probability of any scenario *s*. While the set *s* designates the scenarios (50 in total), *t* refers to the time period (168 hours in total). The parameter η is the storage conversion efficiency. Paramters sin_{max}, $sout_{max}$ and $scap_{max}$ are exogenous characteristics of the storage device, i.e. inflow and outflow limit as well as storage capacity limit. Since the storage is emptied at the last period (equ.3.9), there is no need to assign any left-over value to remaining kWh.

(3.4) $$\max_{SOUT,SIN} \ \pi = 52 \cdot \sum_t \sum_s \begin{bmatrix} prob(s) \cdot \{tariff(t) \ \cdot \ \left(q_{ref}(t,s)\right) \\ - p_{ref}(t) \cdot (q_{ref}(t) + SIN(t,s) - \ SOUT(t,s))\} \end{bmatrix}$$

s.t.:

(3.5) $0 \geq SIN(t,s) \ - \ sin_{max}$ Power limit inflow

(3.6) $0 \ \geq SOUT(t,s) - \ sout_{max}$ Power limit outflow

(3.7) $0 \ \geq \ \sum_{t=1}^{t} SOUT(t,s) - \ \sum_{t=1}^{t-1} SIN(t,s) \cdot \eta$ Storage outflow never exceeds reserve

(3.8) $0 \ \geq \ \sum_{t=1}^{t} SIN(t,s) \cdot \eta - \ \sum_{t=1}^{t-1} SOUT(t,s) - \ scap_{max}$ State of charge never exceeds capacity

(3.9) $0 = \ \sum_{t=1}^{T} SIN(t,s) \cdot \eta - SOUT(t,s)$ Storage balance (zero left-over)

(3.10) $SOUT(t,s) \geq 0; SIN(t,s) \geq 0$ Non-negativity

3.4 Results

Results of our calculations give an impression of yearly contribution margins under varying markup and demand. Figure 17 indicates how these key parameters affect the profitability of a level 3 charging station. It illustrates how the ROI evolves with the markup over electricity prices. For reference, information was included on what tariff rate would correspond to the variable cost level of a 3-liter consuming conventional car (ca. 3.50 EUR/100km). The graph illustrates that a positive project benefit is fairly unlikely if life-cycle investment cost (CAPEX+OPEX) amounts to 94,000. With a markup of 15-30% over marginal cost, as common in the liberalized German electricity sector London Economics (2007), demand at a single station would need to exceed 30 EV/day (600kWh) for the investment to prove beneficial. According to our estimations this would correspond to a fairly unlikely EV adoption rate of more than 3% of the car fleet. Naturally, this number can only be taken as a vague estimate. But it indicates that a station costing 94,000 EUR is far from economic in 2011. On the right side of Figure 17, ROI is depicted at life-cycle investment cost of 54,000 EUR. In this case, a markup of 25% (average tariff 22.83 ct/kWh) yields positive project benefits at demand rates beyond 20 EV/day. Still, this demand rate reflects optimistic projections of approximately more than 2% EV adoption rate. A more likely demand projection of 10 EV/day (> 1% EV adoption rate) requires at least 26.48 ct/kWh average tariff. Concluding from these estimations one could state that fast charging stations at 54,000 EUR total cost require average tariffs above 27.4 ct/kWh (50% mark-up) at EV adoption rates which lie within realistic bounds. The tariff would correspond to a variable cost of roughly 4 EUR per 100 km. When cost figures at 94,000 EUR, charging stations are barely beneficial at usual markup rates. In that case, a charging operator would need to markup by roughly 80% to cover investment cost. If recouping all costs through a charging fee the EV user would pay in average 33 ct/kWh. That rate translates into ca. 4.70 EUR for 100km, hence a value close to variable cost of a state-of-the-art gasoline car. All in all, the estimations suggest that fast charging is unlikely to be economic at EV adoption rates below 1% of the car fleet. However, if localized demand lies above 10 EV/day, electricity could be provided through fast charging at rates which roughly correspond to specific gasoline cost.

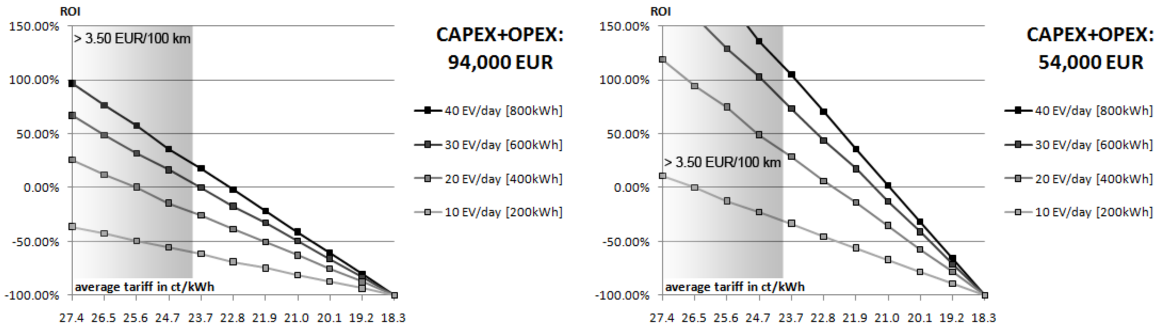

Figure 17: Return on Investment under different investment cost levels.

(Source: Own illustration)

In general, a high local demand for level 3 charging can only be attained if EV users do not exclusively rely on charging facilities at home or at work. It is important for level 3 station operators to ensure there is little competition against alternative charging solutions. Level 3 chargers may be a losing deal even under high EV adoption rates if too few EV users revert to fast charging facilities. The substitution effect between home charging solutions and level 3 charging can be one of the main risk factors determining investment choices. Level 3 charging is therefore likely to be located at spots where there is little competition to home charging. These locations are likely to expose a high share of transit traffic as opposed to commuter traffic, as the latter could mostly rely on inexpensive home charging. Interstate, highway gasoline stations and other stopover locations such as supermarkets and coffee shops could ideally fall into this category.

A crucial question is how to reach the EV penetration rate which renders fast charging solutions financially viable. Some experts argue that the presence of DC charging infrastructure is a prerequisite to a high adoption rate. Corollary to this thinking is that a comprehensive EV charging public infrastructure should be built up if necessary with public financial support. The example of Tokyo shows how DC fast charging technology can spread in supportive political conditions. The findings of this chapter indicate that investment incentives are hitherto too low for a market-driven roll-out. Conversely, there is reason to believe that commitments taken at this premature stage are rather driven by non-financial prospects. Besides, EV stations may be used as a perk to attract consumers while the main revenue is generated from the sale of other products, for instance parking space or commodities. It is pervasive practice for instance at gasoline stations to generate high revenues from non-fuel services.

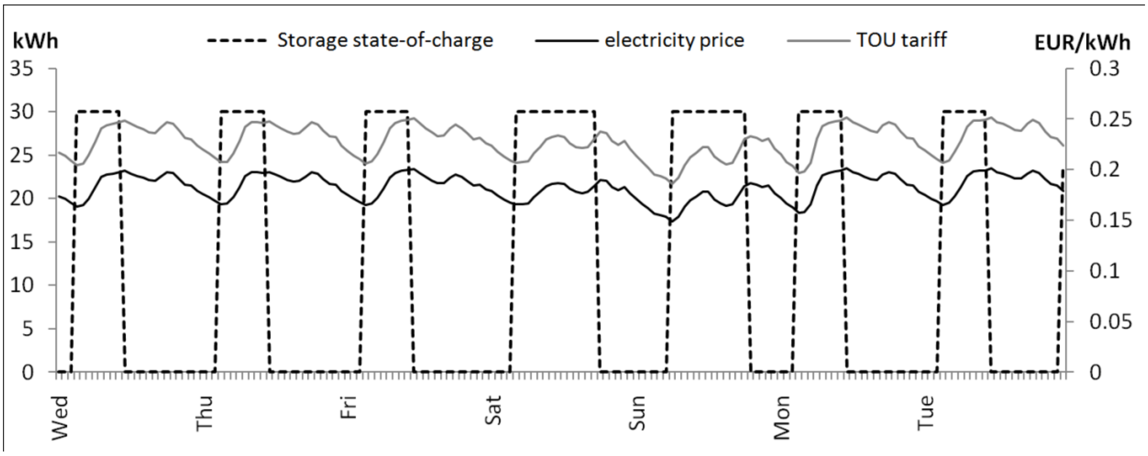

Figure 18: Operation of an on-site storage device of 30 kWh capacity and 30 kW power limit.

(Source: Own illustration)

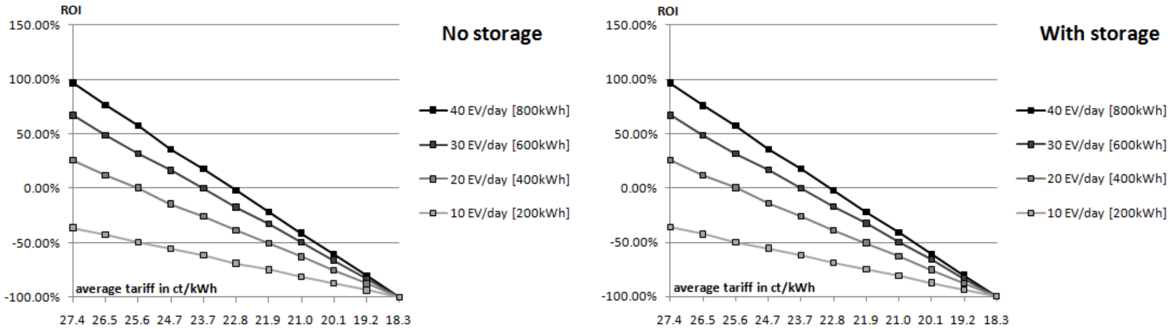

Figure 19: Return on Investment with and without storage.

(Source: Own illustration)

So far, ROI is considered without the use of on-site storage. A storage facility can potentially affect the profitability of charging stations as it is filled at low cost during off-peak times and it is emptied at peak time rates; cf. Figure 18. Arbitrage benefits from a high spread between off-peak purchase at wholesale level and a peak retail tariff. In the case of a public fast charging station, arbitrage can potentially become particularly interesting as retail tariffs can be set much higher than with lower speed charging stations.

In general, the storage unit is not necessarily emptied at times where the tariff is highest but at specific time slots where tariff is highest conditional on that demand is non-zero. This implies that accounting for volatile usage patterns with partly zero demand can diminish the arbitrage value of storage since it confines flexibility to a certain extent.

It is found that the storage unit of 30 kWh is not filled and emptied more than once per day. It can be testified that the use of a different tariff type does not greatly affect the temporal operation of the storage unit. The storage unit is found to improve the revenue stream in average by 3-5%, depending on the tariff used. The revenue boost is countered by a 6.4% cost increase (at 200 EUR/kWh). Figure 19 illustrates that storage hardly affects (in fact slightly deteriorates) ROI of a charging station. The estimations clearly show that on-site storage is unlikely to be a profitable option for charging infrastructure operators. Apparently, the flexibility of storage facilities does not yield a sufficient arbitrage value to cover the high investment cost of batteries, unless a feed-in tariff is provided. This finding echoes Sioshansi et al. (2009) and Sioshansi and Denholm (2010). If at all, storage devices may gain positive value when they are explicitly used for relaxing power flow congestion in low voltage grids. In case fast charging stations are provided and operated through a vertically integrated grid operator and utility, storage units may become an interesting option to sidestep possible grid congestion arising due to extensive use of fast charging during peak times.

While the retail price markup and demand seem to be pivotal for valuing a charging station, the used tariff is equally a big factor. All ROI calculations above were made with a TOU tariff. TOU yields better performance than setting an equivalent flat rate in all scenarios. At 30 EV/day demand, choosing TOU rates instead of a flat rate of equivalent size increases revenue by 4% in average. When an on-site storage system is installed, it is found that the advantage of TOU accentuates to a little extent. Storage seems to yield the greatest improvements if a TOU tariff is used. Clearly, this difference in profits between TOU and flat rate pricing indicates that pricing with temporal price discrimination should be preferred over flat tariffs by a charging system operator. However, simpler tariff structures are likely to be better understood and hence more positively received by consumers than variable prices such as TOU. A compromising option would be to offer tariffs with at least a two-part structure and a sufficient spread. Night rates at below 20 ct/kWh and daytime rates at around 23 ct/kWh, as used at several charging stations in Germany in 2011, appear too low and not sufficiently detailed for a profitable operation of a public charging station.

3.5 Conclusion

This chapter conveys a simple but clear message by means of a straightforward valuation method applied to EV fast charging infrastructure. Besides the mere cost and benefit estimations given in this chapter, four key insights emerge from the analysis.

1) Since less than 20% of all car trips would require fast charging opportunities in an all-electric world, a market-driven roll-out of DC fast charging infrastructure is fairly unlikely to happen at current EV penetration rates. If private investment takes place at this premature stage, it appears to be driven by other than project prospects. Possibly, EV stations may be used just as a perk to attract consumers with main revenue generated from (indirect) non-electricity sales, such as commodity sales or to a certain extent parking fees.

2) While the investment incentive for public fast chargers may turn positive under optimistic circumstances, investment remains fairly risky. One of the main risk factors, besides EV adoption rates, is competition between public and private home charging facilities. Further promotion of home charging boxes deteriorates incentives for investment in public fast chargers.

3) The arbitrage value of an on-site storage facility at quick charging stations is unlikely to cover its own investment cost even under highly marked-up tariffs. This result reflects a general consensus that storage devices hardly pay off through arbitrage in power wholesale markets in the absence of feed-in credits.

4) Tariffs with temporal price discrimination appear to be the most profitable option from an operator’s perspective. However, EV users could possibly prefer simpler rates over erratic TOU tariffs.

3.6 Appendix

	Wednesday		Thursday		Friday		Saturday		Sunday		Monday		Tuesday		
t		kWh	%	kWh	%	kWh	%	kWh	%	kWh	%	kWh	%	kWh	Total
1	0.4%	2.402	0.4%	2.52	0.6%	3.881	1.0%	5.775	0.3%	1.814	0.3%	1.695	0.4%	2.302	20.39
2	0.5%	3.003	0.5%	3.15	0.5%	3.234	0.5%	2.888	0.5%	3.024	0.4%	2.26	0.5%	2.877	20.44
3	1.1%	6.607	1.1%	6.93	0.7%	4.528	0.6%	3.465	1.0%	6.048	1.1%	6.214	1.1%	6.329	40.12
4	2.5%	15.02	2.5%	15.75	1.2%	7.762	1.1%	6.353	2.2%	13.31	2.4%	13.56	2.5%	14.39	86.13
5	4.0%	24.02	4.0%	25.2	2.1%	13.58	1.8%	10.4	3.6%	21.77	3.8%	21.47	4.0%	23.02	139.46
6	4.9%	29.43	4.9%	30.87	3.2%	20.7	2.8%	16.17	4.5%	27.22	4.9%	27.68	4.9%	28.19	180.26
7	5.6%	33.63	5.6%	35.28	4.3%	27.81	3.9%	22.52	5.2%	31.45	5.5%	31.07	5.6%	32.22	213.99
8	5.9%	35.44	5.9%	37.17	5.4%	34.93	5.1%	29.45	5.4%	32.66	5.8%	32.76	5.9%	33.95	236.36
9	5.7%	34.23	5.7%	35.91	6.1%	39.45	6.7%	38.69	5.8%	35.08	5.7%	32.2	5.7%	32.8	248.37
10	5.8%	34.83	5.8%	36.54	6.2%	40.1	7.6%	43.89	6.8%	41.13	5.9%	33.33	5.8%	33.37	263.20
11	5.9%	35.44	5.9%	37.17	6.5%	42.04	7.8%	45.05	7.2%	43.55	6.0%	33.89	5.9%	33.95	271.08
12	6.2%	37.24	6.2%	39.06	6.9%	44.63	7.7%	44.47	7.5%	45.36	6.4%	36.15	6.2%	35.67	282.58
13	6.4%	38.44	6.4%	40.32	7.3%	47.22	7.4%	42.74	7.4%	44.76	6.5%	36.72	6.4%	36.83	287.01
14	6.9%	41.44	6.9%	43.47	7.6%	49.16	7.3%	42.16	7.3%	44.15	7.1%	40.11	6.9%	39.7	300.19
15	7.2%	43.24	7.2%	45.36	7.8%	50.45	7.0%	40.43	7.0%	42.34	7.4%	41.8	7.2%	41.43	305.05
16	7.1%	42.64	7.1%	44.73	7.4%	47.86	6.7%	38.69	6.7%	40.52	7.2%	40.67	7.1%	40.85	295.98
17	6.8%	40.84	6.8%	42.84	6.8%	43.98	6.0%	34.65	5.9%	35.68	6.8%	38.41	6.8%	39.13	275.54
18	5.5%	33.03	5.5%	34.65	5.6%	36.22	5.2%	30.03	4.8%	29.03	5.4%	30.5	5.5%	31.65	225.12
19	4.0%	24.02	4.0%	25.2	4.2%	27.17	4.1%	23.68	3.7%	22.38	4.0%	22.6	4.0%	23.02	168.06
20	3.0%	18.02	3.0%	18.9	3.2%	20.7	3.3%	19.06	2.8%	16.93	2.8%	15.82	3.0%	17.26	126.69
21	2.1%	12.61	2.1%	13.23	2.6%	16.82	2.5%	14.44	2.0%	12.1	2.1%	11.86	2.1%	12.08	93.14
22	1.2%	7.207	1.2%	7.56	1.8%	11.64	1.9%	10.97	1.2%	7.258	1.2%	6.779	1.2%	6.905	58.32
23	0.8%	4.805	0.8%	5.04	1.2%	7.762	1.2%	6.93	0.7%	4.234	0.8%	4.519	0.8%	4.603	37.89
24	0.5%	3.003	0.5%	3.15	0.8%	5.174	0.8%	4.62	0.5%	3.024	0.5%	2.825	0.5%	2.877	24.67
% of week	14.3%		15.0%		15.4%		13.8%		14.4%		13.5%		13.7%		100.00%
Total kwh		600.6		630		646.8		577.5		604.8		564.9		575.4	4200

Figure 20: Estimation of the load pattern of a single charging station over the course of one week. [10]

(Source: Calculations based on data given in Barnes and Liss (2008))

[10] Assumptions: 20 EV/day in average with 20 kWh load demanded in average.

Chapter 4 – An Investment-Dispatch Equilibrium Model with Long-Term Uncertainty

4.1 Introduction and literature review

This chapter investigates the power plant expansion planning of electric utilities under uncertainty about long-term trends in fuel prices. General idea and hypothesis is that expectations of carbon, coal, oil and gas price evolutions are one of the main drivers for investment decisions into power plants (Weber & Swider 2004; Geiger 2010). By reflecting the uncertain nature of the fuel price evolution, we expect to replicate and understand the portfolio effect of investment choices and explain postponement of investment.

Power plant investment decisions are complex and risky given long amortization periods, the volatility of market prices, uncertainty regarding competitors' investment and generation decisions as well as the high regulatory risks. Investments often involve substantial sunk costs, rendering the investment decision almost irreversible. Numerous seminal studies deal with power plant investment decisions without taking appropriate account of uncertainties (dena 2008; EC 2011; EWI et al. 2010). Ninghong et al. (2008) demonstrate how ignoring uncertainties significantly undervalues the operational flexibility and can even result in an insufficient investment into power plants. The representation of uncertainty is thus a prerequisite for a realistic depiction of investment choices.

In principle, two different streams of literature can be found which carry-out quantitative investigations on uncertainties and their impact on investment. One line of literature deals with a detailed treatment of uncertainties through scenario analysis, risk management, decision theory and real options valuation. A second stream of literature deals with a decent treatment of game theoretic aspects, including market analysis and the behavior of competitors. Real options valuation serves as a stepwise solution procedure to investment planning which is able to account for adaptive behavior and learning effects (Dixit & Pindyck 1994). In these real option models, the uncertain parameter evolves according to a random process, firms decide (strategically) on the timing when to install further capacities. While the insights provided are rich in terms of timing, there is a complete abstraction from spot markets and operational inflexibilities. A further caveat of econometric real options valuation is that it hardly takes into account feedback between investment and market interactions (prices) and strategic aspects can be modeled only on a superficial basis. This is where 'fundamental' equilibrium models step in. Equilibrium models as presented in the present chapter can incorporate long-term uncertainty and multi-stage decision-making, thus accounting for the real option character of investment. They depict the relation between costs and the market prices and the ability of firms to adjust their production after investment. At the same time the models allow for a decent depiction of the so-called power dispatch[11] and can include strategic action due to market power, which happened to be relevant for the German electricity market in the recent past (Weigt et al. 2010; Traber & Kemfert 2011a; BNetzA 2011c).

Strategic capacity choices have been extensively discussed in recent literature in a Cournot spot market setting. The liberalization of power markets and the associated issues of oligopolistic market structures and long-term uncertainty have given rise to increased interest in models of strategic power plant investment, partly reflecting uncertainty (Grimm & Zoettl 2008; Murphy & Smeers 2005; Pineau et al. 2011b; Geiger 2010; Genc & Sen 2008), partly deterministic (Ventosa et al. 2002; Pineau et al. 2011a). A more recent trend is the inclusion of firm's risk aversion attitudes into equilibrium models (Ehrenmann & Smeers 2011a; Fan et al. 2010). Table 5 provides an overview of recent work in the field. The interested reader is

[11] Power dispatch refers to the scheduling of power plant commitment.

also referred to Ehrenmann and Smeers (2011b) who include a more extensive review of the use of equilibrium models to analyze power generation capacity expansion equilibria under uncertainty.

All in all, the mentioned works are fairly theory-oriented but modest in their application. There exist virtually only duopoly analysis with few constructive results according to Grimm and Zoettl (2008). In view of the lack of decent applications, we intend to fill this void by providing a case study analysis of the German electricity market with a combined investment and dispatch model. The contribution of our work is to extend the existing electricity market equilibrium model Esymmetry (Traber & Kemfert 2011a) with endogenous investment and include long-term uncertainty. The main research question of this article is how fuel and carbon price risk impact investment decisions. Fuel and carbon prices are one of the major risk factors that utilities face in liberalized markets besides regulatory risk. Adding to the first research question, the investment incentives for utilities are investigated under the current market design and we attempt to answer what level of fuel and CO_2 prices spur investment into the various power plant technologies.

Authors	Title	Year	Model	Critique
Ehrenmann Smeers	Generation Capacity Expansion in a Risky Environment: A Stochastic Equilibrium Analysis	2011	Stochastic, static, Conditional Value at Risk minimization – casted as MCP	Stylized application with 3 technologies, 2 players, static.
Fan, Hobbs, Norman	Risk Aversion and CO_2 Regulatory Uncertainty in Power Generation Investment: Policy and Modeling Implications	2010	Two-Stage stochastic MCP with risk aversion	Simple gas vs. coal firm comparison, static.
Geiger	Strategic Power Plant Investment Planning under Fuel and Carbon Price Uncertainty	2011	Stochastic dynamic programming (LP/Mixed Integer)	No electricity dispatch model.
Genc, Sen	An Analysis of Capacity and Price Trajectories for the Ontario Electricity Market Using Dynamic Nash Equilibrium Under Uncertainty	2008	Stochastic dynamic, Cournot	Real-world application but limited time horizon of 6 consecutive years.
Grimm, Zoettl	Strategic Capacity Choice under Uncertainty: The Impact of Market Structure on Investment and Welfare	2008	Stochastic MCP with oligopolistic structure.	Application to Germany stylized.
Murphy, Smeers	Generation Capacity Expansion in Imperfectly Competitive Restructured Electricity Markets	2005	Stochastic MPEC, Cournot/ Stackelberg, Open & Closed Loop, 1 period	Only 2 players and technologies (base and peak)
Pineau et al.	A Dynamic Oligopolistic Electricity Market with Interdependent Market Segments	2011	Deterministic NLP, 10 year horizon	Only base load vs. peak load and simplistic dispatch model.
Pineau et al.	Impact of Some Parameters on Investments in Oligopolistic Electricity Markets	2011	Stochastic dynamic MCP, Cournot	2 Technologies (base and peak)
Ventosa et al.	Expansion Planning in Electricity Markets. Two Different Approaches	2002	Deterministic NLP/MPEC 11 year horizon	Stylized application.

Table 5: Literature overview in alphabetic order.

(Source: Own illustration)

4.2 Model

The electricity market model is a partial equilibrium model based on the power dispatch model outlined in Traber and Kemfert (2011a). The original dispatch model is complemented with endogenous capacity investment, stochastic elements and a multi-period perspective. The investment planning constitutes an open-loop, multi-period stochastic equilibrium. In open-loop equilibria, all decisions for all stages are set at the start of the game (Basar & Olsder 1999). Strategic decision variables are a sequence of investment and operations. The risk-neutral investor has information on the likeliness of each scenario. Scenarios differ in their assumptions on fuel and carbon prices.

The model is formulated as extensive-form stochastic equilibrium problem. It covers long-term periods (a), short-term time steps for dispatch (t), generation technologies (n) and firms (i). Firms maximize their individual expected and discounted profits π over the modeling period, i.e. revenues net of production costs and fixed investment cost (Equation 4.1). The set of variables comprises investment ($X^{i,n,a}$) as well as ramping ($L^{i,t,n,a}$) and generation decisions ($Q^{i,t,n,a}$). Firms are constrained by a market balance and capacity restrictions for generation and ramping up power generation up to a specific maximum load gradient (Equations 4.2 to 4.7). The market balance ensures that demand net of RES feed-in equals power supply at each point in time. Generation (4.3) and ramping capacity limits (4.4, 4.5) make sure that generation dispatch follows rules imposed by some technical constraints. Equation 4.6 puts an upper limit to investment into specific technologies. The minimum reserve capacity condition (4.7) makes sure that there is sufficient available capacity in the market at any point in time. Equations 4.8 to 4.11 specify the linear demand function, generation cost and the cost of ramping up power generation between two steps in time.

Several firms have the possibility of exerting market power while a competitive fringe is regarded as price taker. This setting makes it necessary to solve the problem as MCP with Karush-Kuhn-Tucker conditions (KKT). The Appendix entails the nomenclature and the KKT conditions (Equations 4.12 - 4.21).

4.1 Profit

$$\max_{Q,X,L} \pi = \sum_{a}^{A} pr^{a}[d^{a}[w^{a}(\sum_{t=1}^{T}\sum_{n=1}^{N}(P^{t,a}(TQ^{t,n,a})Q^{i,t,n,a} - c_{Q}^{n,a}Q^{i,t,n,a} - c_{L}^{n,a}L^{i,t,n,a})) \\ -c_{X}^{n}X^{i,n,a}] + sv^{n,a}X^{i,n,a}]$$

4.2 Market balance

$$P^{t,a} \quad \perp \quad P^{t,a} - \sum_{i=1}^{I}\sum_{n=1}^{N}(p_{0}^{t} - slp^{t,a}(Q^{i,t,n,a} + res^{t,a} - d_{0}^{t})) \geq 0$$

4.3 Generation capacity limit

$$\kappa^{i,t,n,a} \quad \perp \quad (\overline{q}^{i,n,a} + \sum_{a \in pred(a)}^{A} X^{i,n,a})av^{n} - Q^{i,t,n,a} \geq 0$$

4.4 Load gradient upper limit

$$\delta^{i,t,n,a} \quad \perp \quad \overline{l}^{i,t,n,a}(\overline{q}^{i,n,a} + \sum_{a \in pred(a)}^{A} X^{i,n,a})av^{n} - L^{i,t,n,a} \geq 0$$

4.5 Load gradient lower limit

$$\lambda^{i,t,n,a} \quad \perp \quad L^{i,t,n,a} - Q^{i,t,n,a} + Q^{i,t-1,n,a} \geq 0$$

4.6 Capacity expansion limit

$$\rho^{i,n,a} \quad \perp \quad \overline{x}^{i,n} - X^{i,n,a} \geq 0$$

4.7 Reserve energy minimum $$\gamma^{t,a} \quad \perp \quad \sum_{n=1}^{N}\sum_{i=1}^{I}[(\overline{q}^{i,n,a} + \sum_{a\in pred(a)}^{A} X^{i,n,a})av^{n} - Q^{i,t,n,a}] - \underline{q}^{a} \geq 0$$

4.8 Intercept $$int^{t,a} \quad = \quad p_0^{t,a} - d_0^{t,a} slp^{t,a}$$

4.9 Slope $$slp^{t,a} \quad = \quad \frac{p_0^{t,a}}{(d_0^{t,a}\sigma)}$$

4.10 Generation cost $$c_Q^{n,a} \quad = \quad \frac{c_f^{n,a}}{\eta^n} + c_o^n + \frac{emf^n}{\eta^n}\phi^a$$

4.11 Ramping cost $$c_L^{n,a} \quad = \quad s^n c_f^{n,a} + c_d^n + emf^n s^n \phi^a$$

4.3 Application to the German Power Market

The model is applied to the case of Germany with 4 major players exerting market power and a competitive fringe. The model horizon goes from 2010 to 2035 at the investment stage and includes an hourly time resolution at the dispatch stage with a horizon of at least 24h. 14 ‘dispatchable’ generation technologies are considered and RES feed-in is represented as exogenous feed-in. Data is collected to replicate 2010 market behavior and assumptions are made regarding the long-term evolution of key input parameters, in line with Traber and Kemfert (2011a). These key input parameters include investment cost, generation cost, fuel cost, RES feed-in, reference demand, reference spot market prices, discount rate and salvage values. Details can be found in Table 9. Most importantly, World Energy Outlook projections (IEA 2011c) are used to build a scenario structure for fuel and carbon prices as detailed in Figure 2. The IEA scenarios comprise the "current policies scenario", where no policies beyond those adopted in 2011 will be enforced. This scenario translates into high oil and gas prices while carbon prices are low. The "new policies scenario" is somewhat a middling scenario, where more stringent than current policies are adopted notably in the vehicle sector. This scenario is characterized by a moderate price path. On the other extreme, the IEA describes the "450 ppm scenario" as a situation with 50% likelihood of meeting the 2 °C climate policy target. This scenario naturally reflects high carbon prices but low oil and gas prices due to reduced demand. Transition probabilities between scenarios are all set to equal shares throughout all scenario nodes, except in cases where there is only one follower node. As can be seen in Figure 22, we end up with 16 scenario nodes and 6 periods (3 stages) for the time horizon 2015-2035.

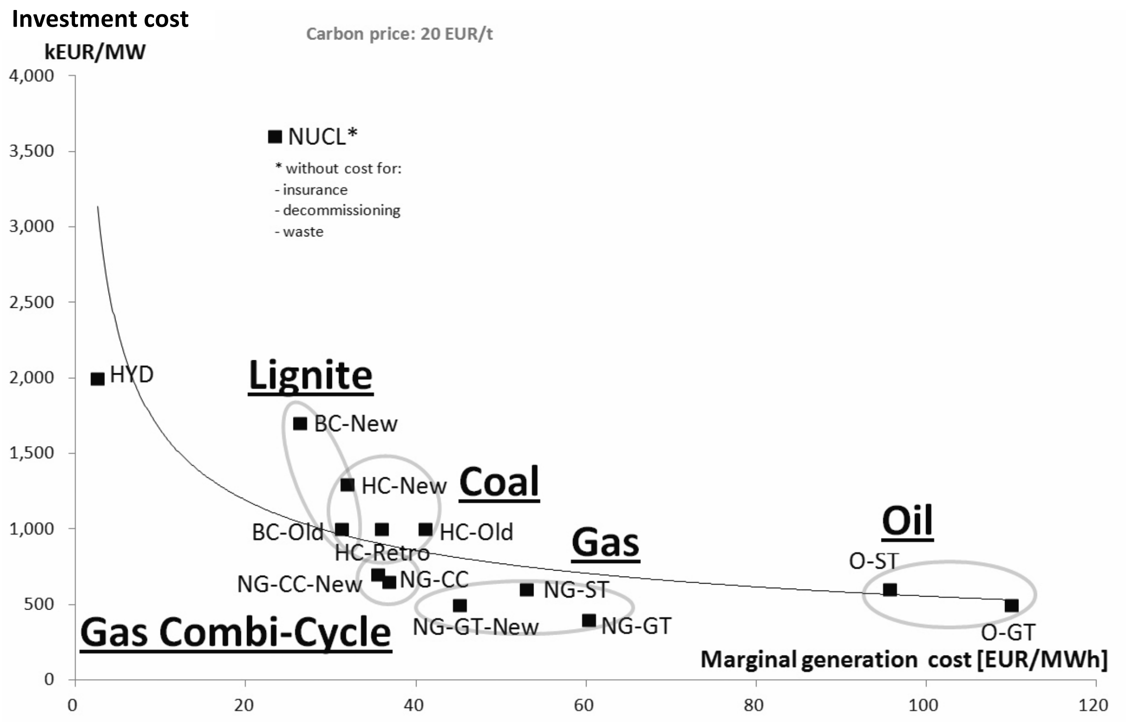

Figure 21: Generation and investment cost.

(Source: Own illustration)

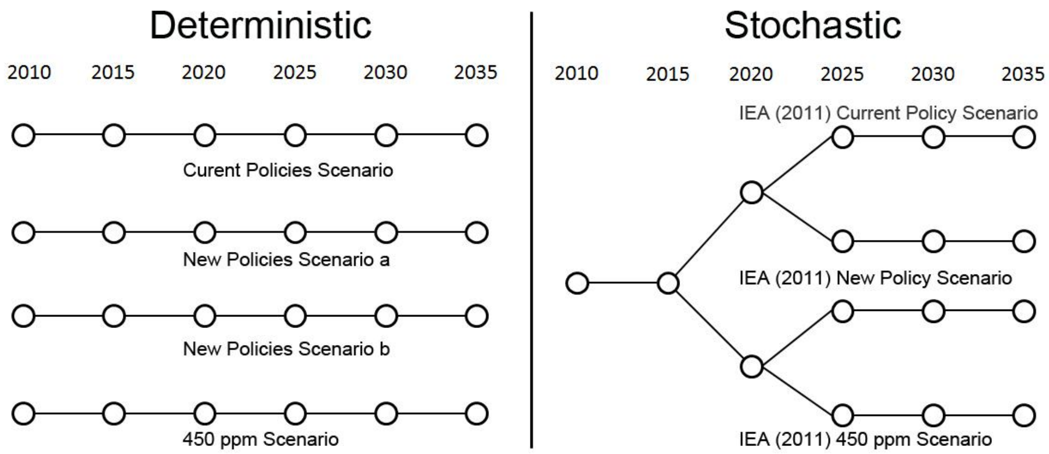

Figure 22: Scenario tree.

(Source: Own illustration)

4.4 Results

In what follows, the extensive-form stochastic problem is compared with its deterministic expected-value counterpart and other forms of deterministic equivalents. The expected value problem corresponds to the average of all scenarios at each stage of the stochastic model. The deterministic perfect information model considers each of the four scenario series separately.

The comparison between stochastic and deterministic models allows for insights into the value that agents would attribute to attaining more certainty and it shows how ignoring uncertainty can lead to lower profits. The results section is sub-divided into an analysis of profits, investments, prices, market structure and a subsequent discussion.

In analyzing the impact of investment risk on the objective value, some basic concepts of stochastic programming are referred to and their outcome is compared. The concept of the value of the stochastic solution (VSS) is commonly used in the stochastic programming community as indicator for the added value of explicitly considering probabilities instead of expected values. Another useful concept is the expected value of perfect information (EVPI). It represents how much one would be willing to pay to receive information on the realization of future events (Birge & Louveaux 1997).

The mixed complementarity program is solved with the PATH solver in GAMS.

4.4.1 Profits

Table 6 shows that profits are highest in the deterministic model under perfect information (EPI). This outcome represents perfect foresight and it is hardly attainable in reality. Naturally, the expected value (ExV) problem and the expectation of the expected value (EEV) problem are both lower than the EPI. They are also lower than the expected stochastic solution (ESS). This is because the stochastic model allows for adaptation to extreme scenario realizations and agents can then perform well in each scenario path. In contrast, the expectation of the EEV allows for no flexibility and the ExV problem entails no extreme events which could raise profits.

(1000EUR)	ESS	ExV	EEV	EPI	VSS		EVPI	
Eon	52,658	49,158	50,257	54,991	2,401	*4.56%*	2,333	*4.24%*
EnBW	28,661	26,849	29,102	32,007	-441	*-1.54%*	3,345	*10.45%*
RWE	42,161	39,470	40,725	45,425	1,436	*3.41%*	3,264	*7.19%*
Vattenfall	41,291	36,798	40,058	44,753	1,232	*2.98%*	3,462	*7.74%*
Dummy	43,106	30,954	28,730	34,844	14,376	*33.35%*	-8,262	*-23.71%*
Total	207,876	183,229	188,872	212,020	19,004	*9.14%*	4,144	*1.95%*

ESS	=	*min E[f(x)]*	Expected stochastic solution
ExV	=	*min f[E(x)]*	Deterministic expected value problem
EEV	=	*E[min f(E(x))]*	Expectation with ExV solution
EPI	=	*E[min f(x)]*	Expectation under perfect information
VSS	=	*ESS - EEV*	Value of the stochastic solution
EVPI	=	*EPI – ESS*	Expected value of perfect information

Table 6: Expected profits over the horizon 2010-2035.

(Source: Own illustration)

Results show how the solutions of the deterministic model perform differently in a "real" stochastic world compared to the predictions of the stochastic model. The VSS is used as indicator how much worse a deterministic model performs in real life and it figures at around

9% in this application, with huge variations across players. For some players, VSS and EVPI are negative. Zhuang (2005) and Egging (2010) explain that such curiosity can occur in equilibrium modeling as opposed to optimization.

4.4.2 Investment

As concerns the optimal decisions of investment sequences, taking into account fuel price risk strengthens the overall level of investment into flexible plants in comparison to the deterministic ExV model (Table 7). This is due to the occurrence of extreme scenarios where agents gain from investing large amounts into one specific technology, once a particular scenario materializes. Another result sound with theory is that investment choices become more diverse in the stochastic model, owing to the portfolio effect. Agents flexibly adapt to newly arising information on scenario realizations and thus choose fairly different technology portfolios at each scenario node, making it overall a diverse mixture of investment choices. In this application, agents invest in new hard coal plants as well as combined cycle gas-fired plants (Table 7). We also see the timing of investment to alter by the presence of imperfect knowledge in a multi-period setting. Agents tend to postpone irreversible investment decisions when holding the option to invest in later periods. As imperfect information unfolds and reduces over time (scenario tree in Figure 22), agents automatically reduce investment risk exposure when postponing decisions.

Stochastic ESS	*(mean values)*	2010	2015	2020	2025	2030	2035	
	CC-New	0	0	6,465	0	0	0	6,465
	HC-New	0	4,500	6,279	50	0	0	10,829
		0	4,500	12,744	50	0	0	17,294

Deterministic ExV		2010	2015	2020	2025	2030	2035	
	CC-New	16,481	0	0	0	0	0	16,481
		16,481	0	0	0	0	0	16,481

Table 7: Investment levels under perfect competition and with 9% discounting.
(Source: Own illustration)[12]

It should be further pointed to the importance of the discounting rate in determining results. Sensitivity analysis shows that discounting has a direct impact on the investment decisions of all players in terms of time, level and also technology choice. In general, the higher the discount rate, the lower is investment into capital-intensive technologies such as coal-fired power. Overall investment levels decrease with increasing discounting rates. Higher discount rates also tend to increase incentives to postpone investment. At later stages, the relation between upfront investment and subsequent revenues becomes smaller due to exponential discounting. All results reported here adopt a 9% real interest rate used for exponential discounting.

[12] 'CC-New' is Gas Combined Cycle; 'HC-New' is a new hard coal-fired plant. Unit is MW.

4.4.3 Prices

Figure 23 shows how price profiles alter over the years in a run with 120 hours at the dispatch stages. Several counteracting drivers affect prices. The increasing availability of low-cost RES dampens prices. However this so-called merit-order effect can be offset when flexible generation units with high variable cost are increasingly called upon. Note that fuel costs tend to rise over time and thus make electricity generation from fossil resources more expensive over time. Additionally, the shortage of power plant capacities can increase the market share of oligopolistic players and thus the ability of exerting market power through capacity withholding. We observe price spikes to be more pronounced in later years and prices are on average higher in later years compared to 2010 reference prices. This finding can be explained by rising fuel prices, the increased use of generation technologies with high variable cost and the more intense ramping regime due to stronger fluctuations in RES feed-in.

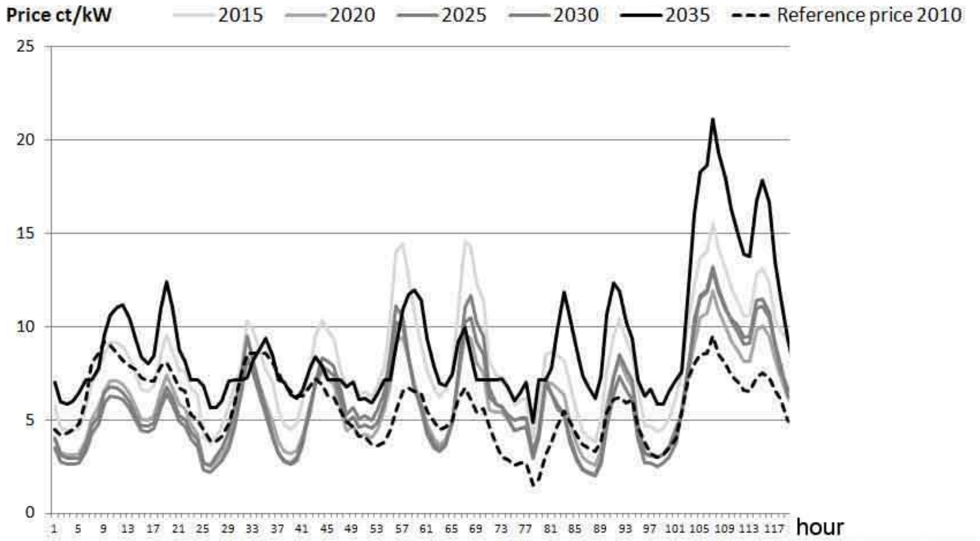

Figure 23: Price profile.

(Source: Own illustration)

4.4.4 Market form

The strategic behavioral assumption of Cournot competition seems far more appropriate than assuming perfect competition. By comparing with historic spot prices from the European Energy Exchange (Figure 23) and historic generation levels, it is clear that Cournot competition results are better in replicating observed prices. This is in line with Traber and Kemfert (2011a) and Weigt and Hirschhausen (2008) which indicate how oligopolistic structures historically affected electricity prices in the German market. For the future, though, it is uncertain whether strategic power continues to be present in the power market since market barriers to new entrants and existing small participants are low in the liberalized market.

Note that accounting for market shares and market power in imperfect markets drives results into a certain direction: It drastically reduces investment of strategic players to zero while investment of the competitive fringe is enhanced to levels beyond the perfect competition case. Overall new capacity rises to ca. 29 GW versus ca. 17 GW in perfect competition.

Although the overall investment level increases, strategic capacity choices of the four dominant market players are consistently lower than in the presence of perfect competition. As a matter of fact, no single investment is performed by oligopolistic players in the Nash-Cournot setting, while we see investments being undertaken by all players in the perfect competition scenario (Table 7). As noted earlier, large strategic firms have a smaller incentive to invest since they expect a price that includes a mark-up in addition to full cost recovery, as opposed to price-taking agents. Since it is questionable whether market power in the power sector prevails in future, and since there are no significant market barriers to investment into new power plants, the analysis here concentrates on the case of perfectly competitive markets and only results from those model runs are reported.

4.5 Conclusions

In this chapter, long-term developments of fuel and carbon prices are analyzed as drivers of investment decisions into thermal power plants. General theory on risk management suggests that agents tend to invest in more (reserve) capacity in stochastic models, but delay investment in a multi-stage setting as uncertainty unfolds over time. Overall, the investment portfolio becomes more diverse with the stochastic model. A stylized application of the model to the German case replicates theory. We show that agents do postpone investment decisions, they increase overall levels of investment, they diversify technology choices and their profits are lower when confronted with uncertainty.

We have provided a framework for the evaluation of investment decisions under long-term uncertainty which helps integrating numerous scenarios in one single model and including security criteria such as minimum system capacity constraints. It was shown that outcomes of investment strategies differ by the type of model used – deterministic or stochastic. The managerial implication is that private investors should take into account long-term uncertainty in integrated stochastic models instead of using scenario analysis with deterministic models. In doing so, investors account for the flexibility in second-stage decision-making after investment. Optimal decisions paths thus differ by the type of model used.

4.6 Appendix

Indices

a	Year (deterministic) or scenario node (stochastic)	
i	Player	
n	Generation technology	
NS	Subset of Nash players i	
Pred	Predecessor node a	
Succ	Successor node a	
t	Hour	

Variables

$L^{(i,t,n,a)}$	Load gradient	MW
$P^{(t,a)}$	Price	EUR
$Q^{(i,t,n,a)}$	Production	MWh
$TQ^{(n,t,a)}$	Total production of all firms	MWh
$X^{(i,n,a)}$	Investment	MW
$\gamma^{(t,a)}$	Shadow price of reserve capacity requirement	EUR/MW
$\delta^{(i,t,n,a)}$	Shadow price of load gradient definition	EUR/MW
$\kappa^{(i,t,n,a)}$	Shadow price of capacity constraint	EUR/MW
$\lambda^{(i,t,n,a)}$	Shadow price of ramp-up constraint	EUR/MW
$\rho^{(i,n,a)}$	Shadow price of capacity expansion limit	EUR/MW
$\theta^{(i,t,a)}$	Market share	%

Parameters

$av^{(n)}$	Availability	%
$c_d^{(n)}$	Marginal depreciation while ramping	EUR/MW
$c_e^{(n,a)}$	Marginal emission cost	t/MWh
$c_f^{(n,a)}$	Fuel cost	EUR/MWh
$c_L^{(n,a)}$	Marginal ramping cost	EUR/MW
$c_o^{(n)}$	Operating cost	EUR/MWh
$c_Q^{(n,a)}$	Marginal cost of generation	EUR/MWh
$c_{re}^{(n,a)}$	Marginal ramping emission cost	t/MW
$c_X^{(n)}$	Investment cost	EUR/MW
$d^{(a)}$	Discount rate	%
$d_0^{(t)}$	Reference demand	EUR
$emf^{(n)}$	Emission factor	t/MWh
$\Phi^{(a)}$	Emission price	EUR/t
$int^{(t,a)}$	Intercept of demand curve	
$bar\{l\}^{(i,n,a)}$	Maximum load gradient	%/hour
$\eta^{(n)}$	Efficiency	%
$p_0^{(t)}$	Reference price	EUR
$pr^{(a)}$	Probability	%
$bar\{q\}^{(i,n,a)}$	Installed capacity	MW
$underline\{q\}^{(a)}$	Minimum reserve capacity requirement	MW
$res^{(t,a)}$	RES and CHP feed-in	MW

$s^{(n)}$	Ramp-up fuel requirement	MWh/MW
$slp^{(t,a)}$	Slope of demand curve	
$sv^{(n,a)}$	Discounted salvage value	EUR
σ	Price elasticity of demand	
$w^{(a)}$	Number of weeks per period	
$bar\{x\}^{(i,n,a)}$	Maximum capacity expansion	MW

Table 8: Nomenclature

(Source: Own compilation)

KKT Conditions

$$pr^a sv^{n,a} - pr^a d^a c_X^n - \rho^{i,n,a} + \sum_{t=1}^{T} \sum_{a \in succ}^{A} (\kappa^{i,t,n,a} + \bar{l}^n \delta^{i,t,n,a} + \gamma^{t,a}) av^n \leq 0 \quad \perp X^{i,n,a}, \forall (i,n,a) \tag{4.12}$$

$$pr^a d^a w^a [P^{t,a} - slp^{t,a} \sum_{n}^{N} Q^{i \in NS,t,n,a} - c_Q^{n,a}] - \lambda^{i,t,n,a} + \lambda^{i,t+1,n,a} - \kappa^{i,t,n,a} - \gamma^{t,a} \leq 0 \quad \perp Q^{i,t,n,a}, \forall (i,t,n,a) \tag{4.13}$$

$$-pr^a d^a w^a c_L^{n,a} + \lambda^{i,t,n,a} - \delta^{i,t,n,a} \leq 0 \quad \perp L^{i,t,n,a}, \forall (i, t > 1, n, a) \tag{4.14}$$

$$P^{t,a} - \sum_{i=1}^{I} \sum_{n=1}^{N} (p_0^t - slp^{t,a}(Q^{i,t,n,a} + res^{t,a} - d_0^t)) = 0 \quad \perp P^{t,a}, \forall (t,a) \tag{4.15}$$

$$(\bar{q}^{i,n,a} + \sum_{a \in pred(a)}^{A} X^{i,n,a}) av^n - Q^{i,n,t,a} \geq 0 \quad \perp \kappa^{i,t,n,a}, \forall (i,t,n,a) \tag{4.16}$$

$$\bar{l}^n (\bar{q}^{i,n,a} + \sum_{a \in pred(a)}^{A} X^{i,n,a}) av^n - L^{i,t,n,a} \geq 0 \quad \perp \delta^{i,t,n,a}, \forall (i, t > 1, n, a) \tag{4.17}$$

$$L^{i,t,n,a} - Q^{i,t,n,a} + Q^{i,t-1,n,a} \geq 0 \quad \perp \lambda^{i,t,n,a}, \forall (i, t > 1, n, a) \tag{4.18}$$

$$\theta^{i,t,a} (\sum_{i \in NS^i}^{I} \sum_{n=1}^{N} Q^{i,t,n,a}) - \sum_{n=1}^{N} Q^{i,t,n,a} = 0 \quad \perp \theta^{i,t,a}, \forall (i \in NS, t, a) \tag{4.19}$$

$$\overline{x}^{i,n} - X^{i,n,a} \geq 0 \quad \perp \rho^{i,n,a}, \forall (i,n,a) \tag{4.20}$$

$$\sum_{n=1}^{N} \sum_{i=1}^{I} (\overline{q}^{i,n,a} - Q^{i,t,n,a}) - \underline{q}^a \geq 0 \quad \perp \gamma^{t,a} \tag{4.21}$$

		Investment cost	Fuel emission (d)	Efficiency (d)	O & M costs (d)	Ramp-up fuel (d)	Ramp-up depreciation (d)	Maximum load gradient (g)	Available (d)	Fuel price (f)
		kEUR/MW	kg/kWh	%	ct/kWh	kWh/kW	ct/kW	%/hour	%	ct/kWh
Pumped hydro	HYD	-	0	1	0.26	0	0	100	75	0.00
Nuclear	NUC-L	-	0	0.34	0.1	16.7	0.17	15	86	0.76
Lignite	BC-Old	-	0.4	0.38	0.26	6.2	0.1	40	85	0.29
Lignite new	BC-New	1700 [1950 (b)]	0.4	0.43	0.1	6	0.3	50	100	0.29
Coal old	HC-Old	1300 (b) [800 (e)]	0.34	0.34	0.2	6.2	0.15	40	82	0.65
Coal retrofit	HC-Retro	1100	0.34	0.38	0.1	6	0.5	40	100	0.65
Coal new	HC-New	1300 [1950 (a), 2250 (b)]	0.34	0.43	0.1	5.5	0.5	50	100	0.65
Gas combi cycle old	NG-CC	650	0.2	0.58	0.13	3.5	1	50	86	1.66
Gas combi cycle new	NG-CC-New	700 [950(b), 530 (f)]	0.2	0.6	0.12	2.9	1	55	90	1.66
Gas steam turbine	NG-ST	600	0.2	0.4	0.15	4	1	36	86	1.66
Gas gas turbine old	NG-GT	400 (b)	0.2	0.35	0.15	1.1	1	100	86	1.66
Gas gas turbine new	NG-GT-New	500 [400(b)]	0.2	0.47	0.13	1.1	1	100	90	1.66
Oil steam turbine	O-ST	600	0.28	0.38	0.15	4	0.5	36	84	3.02
Oil gas turbine	O-GT	500	0.28	0.33	0.15	1.1	0.5	100	84	3.02

a) (IEA et al. 2010) – exchange rate EUR-USD 1.33
b) (EWI et al. 2010) – for 2020
c) (Konstantin 2007)
d) (Traber & Kemfert 2011a)
e) (Genc & Sen 2008)– exchange rate EUR-USD 1.33
f) (IEA 2011c)
g) (IEA 2011b)

Table 9: Technical and economic parameters

(Source: Own compilation)

Chapter 5 – An Investment-Dispatch Equilibrium Model Applied to Europe

5.1 Introduction

This chapter presents results gained from the model “EMELIE-ESY”, a partial equilibrium model with focus on electricity markets where private investors optimize their generation capacity investment and the hourly operation of power plants (‘dispatch’) over a long-term horizon up to 2050. EMELIE stands for Electricity Market Liberalization in Europe - ESY refers to energy symmetry in regard to supply and demand. The contribution forms part of the Energy Modeling Forum 28 (EMF28) study which is based on a comparison of results from a variety of well documented energy models. The study focuses on the impact of energy technology availability on the costs of achieving European climate policy targets with different stringencies of the emission trading system. The model EMELIE-ESY participates in the EMF28 model comparison with a partial equilibrium model to gain detailed sector-specific perspectives. A distinctive feature of EMELIE-ESY is that investments in power capacities are driven by market clearing prices received by private investors on a basically free electricity market with expansion restrictions and at the high expected private discount rate of 8% in real values, common for long term private investments in the sector. Furthermore, the model includes the effect of power plant ramp-up restrictions on the hourly supply profile of an exemplary day and the consequent impact on price profiles in each country.

In the model application presented here fundamental determinants of investment and dispatch decisions are investigated. The EMF28 scenario set-up is used in assessing the implications of climate policy targets and technology availability on technology choices for conventional power plants. We study the impact of climate policies and technology availability on market outcomes with regard to investment choices and the power mix. We find that the European electricity sector will be able to meet stringent climate policy targets without relying on contentious technologies such as nuclear power and Carbon Capture and Storage (CCS) if an accelerated role out of renewable energy sources (RES) is realized. EMELIE-ESY demonstrates how the conventional power sector develops under these targets relying on forces induced by power and emissions markets.

After the introduction, key model features are outlined and the different scenarios are explained. The results are presented, followed by a conclusion.

5.2 Model

The EMELIE-ESY model is a partial equilibrium model of the power sector. Aiming for profit maximization, numerous agents make investment decisions for conventional technologies and dispatch decisions. EMELIE-ESY combines the investment model EMELIE (Traber & Kemfert 2011b) and the dispatch model ESYMMETRY (Traber & Kemfert 2011a). It hence constitutes an integrated multi-period investment-dispatch model, coded as MCP in GAMS software. The algebra of the model formulation is presented in Traber and Kemfert (2012) and resembles the one of the model used in the previous chapter. Input parameters regarding economic and technical parameters are largely in line with a study prepared by Schroeder et al. (2013).

5.2.1 Regional resolution

In terms of regional resolution, the model application includes all countries of the EU-27 plus Norway and Switzerland. Figure 24 provides an overview of the regional disaggregation. Spain and Portugal are grouped into IBERIA; Great Britain and Ireland are included as British

Isles; Denmark, Sweden, and Finland constitute the regional aggregate NORDIC; Lithuania, Latvia, and Estonia are represented as BALTIC, while the group SOUTHEAST comprises Slovakia, Slovenia, Hungary, Romania, Bulgaria, and Greece. Finally, Belgium and Luxemburg are merged in one group.

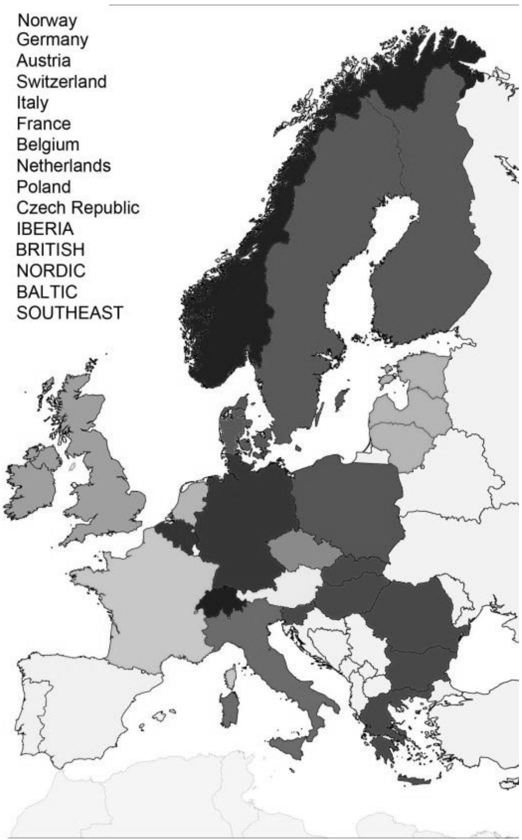

Figure 24: Regional resolution of EMELIE-ESY

(Source: Own illustration)

5.2.2 Temporal resolution

The temporal coverage is five 10-year periods representing the range from 2010 to 2050. Each 10-year period encompasses a dispatch stage represented by 24 consecutive hours. Hence, each 10-year period is represented by one representative day in hourly resolution. The set-up of 10-year periods and hourly dispatch is chosen to combine long-term and short-term elements of investment planning. We should note that a representative day at the dispatch stage does not take into account less probable extreme events such as extremely low production of wind power.

5.2.3 Transmission

The projections of the grid structure and corresponding Net Transfer Capacities (NTC) between countries are taken from ENTSO-E (2012). Winter and Summer NTCs are taken to build averages. The expansion of the grid is line with indications in the EC Roadmap (EC 2011). The EMELIE-ESY model represents import-export-transfers between countries in a piping model with scarcity pricing as outlined in Traber and Kemfert (2012). Scarcity pricing refers to the fact that transmission line congestion effects are priced into market prices. The piping model considers that electricity trade patterns disregarding physical flow characteristics such as loop flows.

5.3 Scenarios

The scenarios were predetermined within the EMF28 group. They are grouped along a technology availability dimension (horizontal) and a policy dimension (vertical). Table 10 provides an overview of the 10 scenarios and their abbreviations used hereafter.

The policy dimension essentially prescribes a reduction of greenhouse gas emissions until 2050 by 40% in the reference case and by 80% in the mitigation scenario, respectively compared to values of 1990. These policies are implemented in EMELIE-ESY by emission caps for the electricity sector. The reduction path for the power sector is actually tighter than the economy-wide path with targets of 40% or 80% by 2050. In line with the Energy Roadmap of the European Commission (EC 2011), we use targets which gradually reduce the carbon emission of the electricity sector by two thirds in the reference case and by 97.2% in the mitigation scenario compared to sectoral carbon emissions in 2010 (1.265 GT CO_2).

The specifications of technology scenarios are further detailed in the subsections hereafter.

	Default w CCS	**Default w/o CCS**	**Pessimistic**	**Optimistic**	**Green**
CCS	on	off	off	on	off
Nuclear energy	reference	reference	low	reference	low
Energy efficiency	reference	reference	reference	high	high
Renewable energies	reference	reference	reference	reference	optimistic
Reference: including the 2020 targets and 40% CO_2 reduction by 2050	*40%DEF*	*40%noCCS*	*40%PESS*	*40%EFF*	*40%GREEN*
Mitigation: 80% CO_2 reduction by 2050 (with Cap&Trade within the EU)	*80%DEF*	*80%noCCS*	*80%PESS*	*80%EFF*	*80%GREEN*

Table 10: Scenario overview

(Source: Own illustration)

5.3.1 Demand and energy efficiency

Electricity consumption is endogenous and represented with linear, country-specific demand functions which are constructed around a reference point representing historic realizations of consumption and prices. Price-elasticity of demand at the reference point is set to 0.3 throughout all time periods and regions. Regarding reference demand, average hourly demand values of the year 2010 published by ENTSOE are used. Starting from reference prices and consumption of the year 2010, reference consumption is set to increase by 10% per decade for OECD countries and 20% per decade for non-OECD countries in all scenarios where energy efficiency is set to “reference”. In the energy efficiency “high” scenario, reference demand only grows by 5% and 10% per decade respectively.

Reference spot market (day ahead) prices are taken from several European energy exchanges. We use Nordpool prices for the specification of the Norwegian, Nordic and Baltic markets. Poland and the Czech Republic are assigned Polish Power Exchange prices (exchange rate 4.2 PLN/EUR). SWISSIX prices are used for Switzerland. The remaining regions are assigned

Phelix EEX power prices. Reference consumption is based on values published by ENTSO-E. The values for the German market are adjusted for the consumption of railroads and industries not connected to the public grid and therefore not accounted for by ENTSO-E.

5.3.2 Renewable energy

RES capacities, i.e. wind, solar, biomass, and hydro are treated as exogenous feed-in based on the National Renewable Energy Action Plans (NREAPs) up to 2020, and a trend projection until 2050 (EEA 2012). Their hourly supply profile is fixed in each scenario and based on the average German profiles, scaled to the generation values of the NREAPs to represent different regions. Beyond the NREAPs projections of 2020, we assume a linear trend expansion of the RES capacities up to 2050 in the renewable energy reference ("reference") case. In the scenarios with "optimistic" RES development, the growth of production is double the growth in the reference scenarios in absolute terms.

5.3.3 Conventional generation

On the supply side, the dispatch of conventional generation - including hydro power - is modeled endogenously. Up to 14 'dispatchable' generation technologies are reflected in the model as indicated in Table 11. Coal-fired plants are sub-divided by boiler criticality, fuel type and CCS availability. Gas- and oil-fired plants are divided by turbine type. Nuclear power plants are distinguished by vintage, in order to reflect evolutions from ordinary generation III reactors towards new-type reactors such as EPR and AP-1000.

The availability of generation technologies differs across scenarios as outlined in Table 10. "Off" denotes the non-possibility of investment into CCS technology. "On" refers to the availability of CCS in certain countries. For nuclear power, "low" means there is no possibility of new-built nuclear power plants in any country. In the "reference" case, upper limits for investment into nuclear power are set at either the level of currently planned projects or the amount of power plants decommissioned after 50 years of operation – depending on which number is greater. These limits are constructed so as to allow countries to at least keep their current nuclear capacity levels and possibly expand their capacity, if current plans of new built exist.

Investment cost ranges between 6000 EUR/kW for new EPR nuclear reactors to 400 EUR/kW single cycle gas turbines (Gas GT) (Schroeder et al. 2013). Following the assumed potential for technological development, investment costs of CCS-Technologies, nuclear reactors and combined cycle gas turbines show a decreasing cost trend, whereas investment costs of mature technologies have constant investment cost expressed in current monetary value.

We further distinguish generation technologies by technological characteristics such as efficiency, operation and maintenance costs, start-up fuel requirements, ramping limits, fuel emissions, start-up depreciation and availability. Values are fixed over the model time horizon as laid out in Table 11. Note that O&M costs for nuclear power include a surcharge for nuclear waste disposal, as detailed in Schroeder et al. (2013). Ramping restrictions are reflected at the dispatch stage in order to represent inflexibilities in the scheduling of power plant commitment.

Major drivers of the full costs of generation are fuel prices. In order to attain model comparability, we follow fuel price assumption in line with IEA projections (IEA 2011d) and closely in line with partner models as laid out in Table 11.

Group	Description	EMF28 Denomination	Investment cost in EUR_{2010}/kW				
			2010	2020	2030	2040	2050
Nuclear	Generation 3 Old Nuclear	Nuclear	6000	5833	5671	5513	5360
	Generation 3 EPR Nuclear	Nuclear	-	-	-	-	-
Coal	Lignite Subcritical	Coal|PC|w/o CCS	-	-	-	-	-
	Lignite Supercritical	Coal|PC|w/o CCS	1700	1700	1700	1700	1700
	Old Subcritical	Coal|PC|w/o CCS	-	-	-	-	-
	Coal Supercritical	Coal|PC|w/o CCS	1300	1300	1300	1300	1300
	Lignite Oxyfuel CCS	Coal|PC|w CCS	3881	3577	3296	3038	2800
	Coal IGCC CCS	Coal|IGCC|w CCS	2988	2794	2613	2443	2285
Gas	Gas Precombustion CCS	Gas|CC|w CCS	1637	1528	1425	1330	1241
	Gas Combined Cycle	Gas|CC|w/o CCS	800	764	729	696	664
	Gas Combustion Turbine	Gas|CT	400	400	400	400	400
	Gas Steam Turbine	Gas|CT	-	-	-	-	-
Oil	Oil Steam Turbine	Oil|w/o CCS	-	-	-	-	-
	Oil Combustion Turbine	Oil|w/o CCS	-	-	-	-	-
Hydro	Hydroelectric	-	-	-	-	-	-

	Efficiency [%]	O&M costs [cent/kWh]	Start-up fuel [kWh/kW]	Maximum load gradient [%/hour]	Fuel emission [kg/kWh]	Start-up depreciation [cent/kW]	Availability [%]
Nuclear	0.34	1.8	16.7	0.04	0.00	0.5	0.81
Coal CCS	0.40	3.6	8.0	0.30	0.04	0.5	0.84
Coal	0.46	0.6	6.2	0.30	0.35	0.5	0.82
Lignite	0.43	0.6	6.2	0.08	0.40	0.3	0.85
Lignite CCS	0.31	4.1	8.0	0.08	0.05	0.3	0.87
Gas CCS	0.48	1.9	2.0	0.30	0.02	1.0	0.92
Gas CC	0.60	0.2	2.0	0.50	0.20	1.0	0.92
Gas GT	0.45	0.2	1.1	1.00	0.20	0.5	0.92

EUR_{2010}/ MWh_{fuel}	2010	2020	2030	2040	2050
Lignite	0.3	0.4	0.4	0.5	0.5
Hard Coal	1.3	1.3	1.4	1.6	1.7
Natural Gas	2.3	3.0	3.4	3.7	4.1
Uranium	0.2	0.2	0.2	0.2	0.2

Table 11: Technological characteristics and fuel price assumptions

(Source: Own illustration)

The decommissioning of existing generation capacity is set exogenously in line with existing and near-term planning up to 2020 as indicated in the Platts database (Platts 2011). For the period from 2030 onwards, we use a heuristic to approximate limits for new investments based on the replacement of retiring capacities. More precisely, natural gas and hard coal investments are allowed to overcompensate the decommissioning according to lifetime expectancy by 100%, while investments in lignite capacities may at most replace decommissioning. In the scenarios denoted “reference” nuclear technology construction is confined to currently planned projects until 2020 or to the amount of decommissioned capacity in the corresponding decade if the latter number is greater. For the decades following 2020 current plans until 2020 are used as a proxy for planning. Only in Germany, decommissioning of old capacities does not imply the option of new investments. Notably, this scenario disregards policy decisions taken in countries like Belgium and Sweden and, thus, indicates an optimistic potential for nuclear investments. By contrast, in the scenario nuclear “low” nuclear production relies on existing capacities or plants currently under construction which are decommissioned after 50 years of lifetime or according to the German nuclear phase-out policy. Finally, CCS in scenario “reference” follows the expansion limits of ordinary gas and coal plants as indicated above, whereas the scenario CCS “off” does not allow for construction of CCS power plants.

5.4 Results

Results are compared most explicitly to the models PRIMES and POLES. PRIMES is the reference model since it is frequently used by the European Commission, for instance for the EU Energy Roadmap (EC 2011). POLES is used as reference because of its similar format as partial equilibrium model with detailed treatment of power markets.

5.4.1 Wholesale spot price projections

EMELIE-ESY is designed to calculate plausible electricity wholesale prices in the long run. The model therefore relies on long-run marginal cost pricing plus an additional price component which reflects ramping costs of power plants. Therefore, modeled electricity prices cover all costs for the operators and investors of the marginal power plant, i.e. the investment which breaks even with a return of 8% per year.

The comparison of the average volume weighted wholesale electricity price projections in Figure 25 essentially reveals three distinct pathways. They range from a pronounced increase of 190% until 2050 compared to 2010 in the most pessimistic scenario 80%PESS to the scenario 40%GREEN, in which prices increase 20% between 2010 and 2050. High energy efficiency and an accelerated RES roll-out in 40%GREEN alleviate price increases. As variable fuel cost of a gas-fired power station increase by about 110% until 2050 and given the reduction of plant utilization induced by RES, it follows that the profitability of a gas power station significantly reduces over time in 40%GREEN.

Between the two extreme cases we observe an intermediate price path in scenarios with high energy efficiency and either a less ambitious climate policy (40%EFF) or a high RES roll out (80%GREEN), which lead to price increases of 81% and 59%, respectively. Prices drift apart from the high price scenarios 80%PESS/80%DEF/40%DEF as of 2020. The high price scenarios either assume a less ambitious climate policy (40%DEF) or a combination of low increases in energy efficiency with (80%DEF) or without (80%PESS) the option of nuclear power plant construction. The difference of the latter scenarios is the wholesale price effect of newly built nuclear power plants, which amounts to 27% of the price level in the first period. Finally, the price projection of scenario 80%EFF (not shown) corresponds closely to the development in 80%DEF. This indicates the potential of increased energy efficiency to compensate price effects induced by more stringent climate policy under our assumptions.

Prices in other EMF 28 models differ in the way they are composed and in their type (wholesale versus end-user prices, average versus maximum). A rough comparison of results shows that electricity prices calculated by EMELIE-ESY are higher as compared to most other models in a variety of scenarios. The prices reported by other models often seem to not cover full cost of investment. Instead, investment seems to be triggered even at low producer prices due to minimum capacity constraints and implicit additional revenue components. However, a pronounced electricity consumption increase in POLES and PRIMES (Figure 28) occurs despite significant increases in the fuel and investment costs of marginal power plants, which opens up a question with regard to the demand elasticity used in those models.

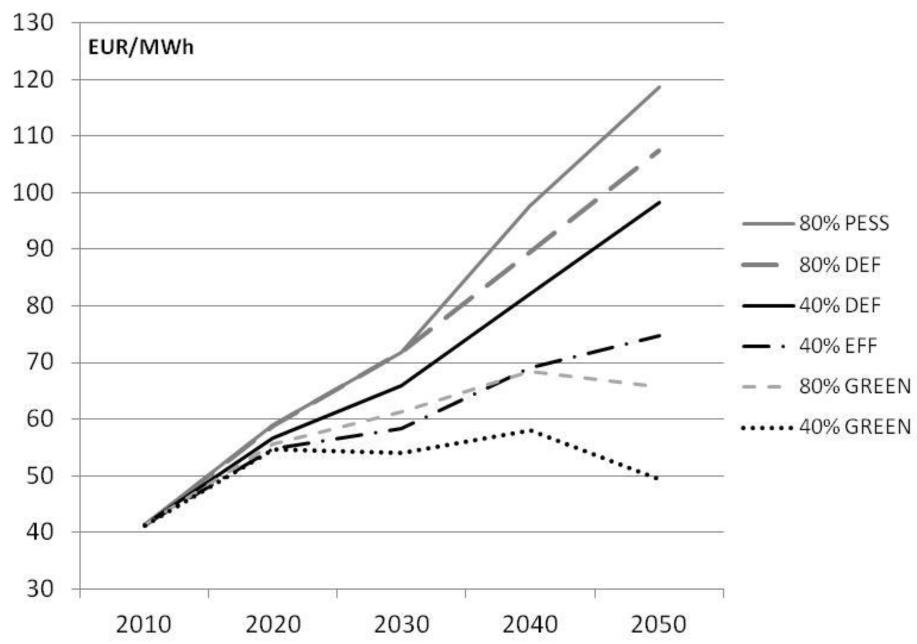

Figure 25: Wholesale electricity prices EU-27 average

(Source: Own illustration)

5.4.2 Emission market prices

Our results on emission prices under the European Union Emission Trading System (EU ETS) correlate closely with the wholesale power price developments. Notably in the scenario 40%GREEN with a more ambitious RES roll out and less ambitious climate policy we find a decreasing price path after 2020 as laid out in Figure 26.

The comparison of our findings with POLES and PRIMES shows that the models compute similar emission prices in the reference scenarios in both climate policy cases at least until 2040. Under reference climate policy and reference technology assumptions of scenario 40%DEF, the emission price projection of EMELIE-ESY shows only a slightly more pronounced increase with an emission price of 65 EUR/t of CO_2. To the contrary, the closely related emission price pathways of POLES and PRIMES deviate significantly from our results in the ambitious climate policy scenario 80%DEF. In scenarios 80%DEF, 80%PESS and 80%GREEN we find comparatively less accentuated emission prices with maximal values ranging between 98 and 192 EUR/t by 2050. In the same scenario group POLES reports emission prices of between 240 and 3629 EUR/t by 2050, whereas PRIMES respective results are between 270 and 290 EUR/t.

The wide range of emission prices across scenarios highlights shows the sensitive nature of emission prices in EMELIE-ESY. In particular, the difference in emission prices between scenarios 80%DEF and 80%PESS (65 EUR/t by 2050) reveals a sensitivity of the model with regard to the availability of a nuclear power option. The corresponding emission price reduction induced by the availability of nuclear power and CCS technology is 12 EUR/t in the PRIMES model. All comparative values have to be interpreted against the backdrop of much higher nuclear power plant investments in POLES and PRIMES.

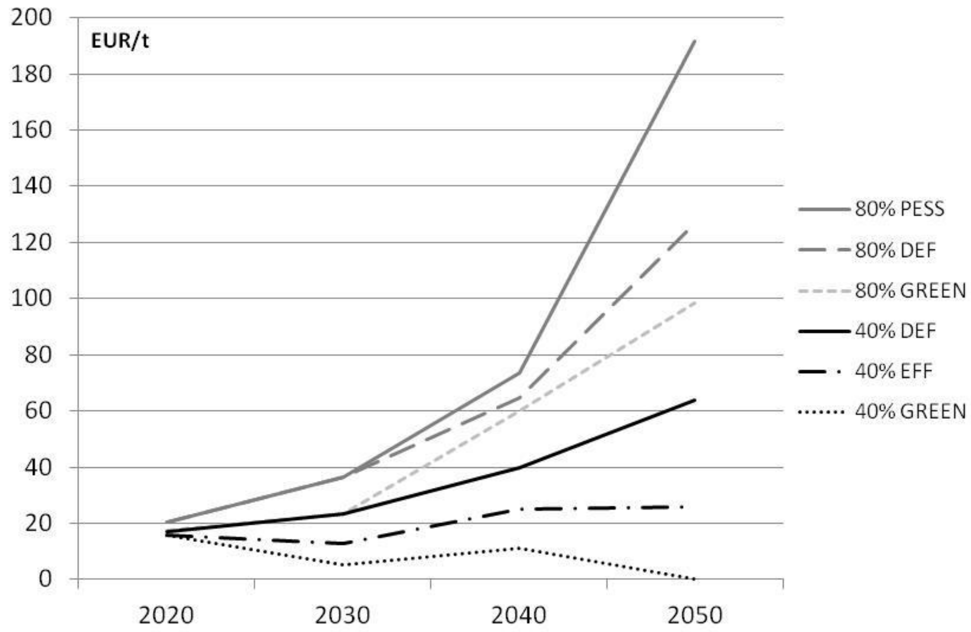

Figure 26: Carbon emission prices

(Source: Own illustration)

5.4.3 Market-driven capacity evolution

Investment pathes for conventional generation technologies differ significantly across scenarios. Figure 28 gives details on the investment in new conventional power plants in the EU-27. We observe identical outcomes for scenarios 40%DEF/NOCCS/PESS, and for scenarios 80%DEF/NOCCS. As no investment into CCS technology materializes, identical outcomes are computed in the scenario pairs 40%DEF/NOCCS and 80%DEF/NOCCS. Furthermore, there are no investments in nuclear energy in scenario 40%DEF. It is therefore not necessary to separately consider scenarios 40%NOCCS, 40%PESS and 80%NOCCS as they can be represented by Scenarios 40%DEF, and 80%DEF. Furthermore, one can categorize the scenarios into two groups by considering overall conventional capacity investment levels until 2050. One group comprises scenarios 40%DEF to 80%DEF where between 60 and 85 GW of new conventional capacities are constructed. In the second group of remaining scenarios 80%PESS to 80%GREEN only 21 to 37 GW of conventional technologies are incentivized by the markets. New nuclear power plants are only built in the ambitious policy scenario with low energy efficiency and less ambitious RES roll-out in 80%DEF/NOCCS. In scenario 80%DEF the model suggests 49 GW of nuclear power plant investment in 80%DEF. Coal fired power plant projects seem to be not impacted by the availability of nuclear power technology. Consequently, total new built capacity reduces by 50% from 75 GW in scenario 80%DEF to about 38 GW in scenario 80%PESS.

Moreover, the scenarios of high energy efficiency suggest similar capacity developments, i.e. within pair 40%EFF/GREEN and pair 80%EFF/GREEN. Differences within these pairs are only due to the extent of power generation from RES and to the availability of nuclear power. Since the latter plays no role in the non-ambitious emission policy scenario, differences between scenario 40%EFF and 40%GREEN indicate the effect of a pronounced RES roll out and lead to minor differences in timing and technology choice between gas and coal. In scenario 40%GREEN slightly more coal fired power plants are constructed in the last model period 2050, displacing some investment in gas fired power plants. Likewise, minor differences are obtained for scenarios 80%EFF and 80%GREEN. In 80%EFF we find investment in barely 2 GW of nuclear power. In 80%GREEN the non-availability of nuclear investment options is partially compensated by about 1 GW higher natural gas investment.

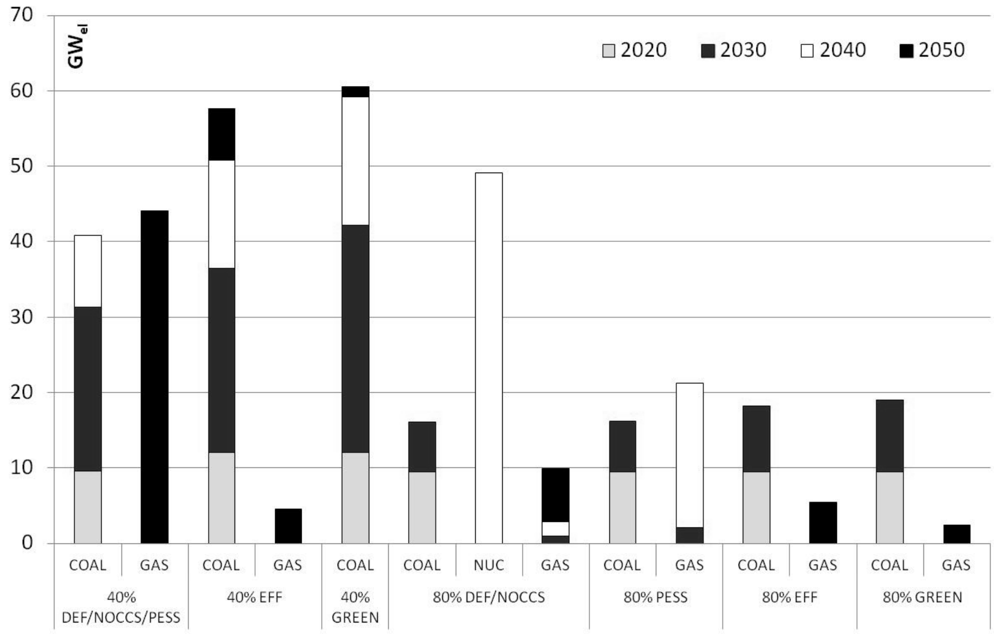

Figure 27: Conventional capacity investments until 2050 [GW_{el} net capacity].

(Source: Own illustration)

In total, future installed capacities in PRIMES and POLES are significantly higher than in EMELIE-ESY although RES input is relatively similar across all models. Most notably, PRIMES and POLES set themselves apart from EMELIE-ESY in that they are comparatively optimistic on the deployment of CCS technology for both, gas and coal power plants. PRIMES projects for both scenarios 40%DEF and 80%DEF around 50 to 60 GW of CCS-equipped coal-fired power plants in the EU by 2050. Moreover, PRIMES calculates with investment into Gas CCS power plants of around 142 GW in the stringent climate policy scenario 80%DEF and 41 GW in the 40%DEF scenario by 2050, respectively. Emission prices of the EU ETS as well as the development of electricity consumption can partly explain these differences.

Similarly, installed nuclear power plant capacity by the year 2050 differs significantly across the compared models. Whereas EMELIE-ESY calculates an installed capacity of 21 GW in scenario 40%DEF, and 72 GW under stringent climate policy, the respective values range between 102 and 156 GW in PRIMES and POLES. Two drivers of these differences can be identified: First and foremost, the investment costs of nuclear power plants is up to 50% lower in POLES, and up to 25% lower in PRIMES, notably in the early periods of the time horizon. Adding to this, variable cost of 25 EUR/MWh for nuclear power are higher in EMELIE-ESY than in any other model. Secondly, the demand development in EMELIE-ESY is dampened by high prices, whereas other models, e.g. PRIMES and POLES, project an escalating consumption of electricity.

We observe very low new built conventional capacity investments in our model in the scenarios of ambitious climate policy without the option of nuclear energy (80%PESS/80%EFF/80%GREEN). We shall stress at this point that our model does not per se provide sufficient capacities to meet system reliability or adequacy but it represents an 'energy-only' market. Investors must recoup their investment cost by the pure sales of energy without generating any additional revenues from any other service (i.e. no capacity payments, no ancillary services). We presume that system requirements are likely to be fulfilled by cheap single cycle gas turbines and stronger network integration in Europe.

Overall, the results of the EMELIE-ESY model indicate that even a low-carbon EU is likely to see relatively little private investor engagement in CCS technology, nuclear, coal-fired and new gas-fired plants in most European countries. This holds even though market prices continue to rise steadily in most countries. Besides the effect of overall demand growth as key driver of investment, we explain the low investment level by implicit assumptions regarding investment incentives. Investment behavior in the EMELIE-ESY model is market-driven assuming the current market design without capacity instruments and system stability requirements for private investors. In comparable peer models, system stability requirements are crucial regarding capacity investment.

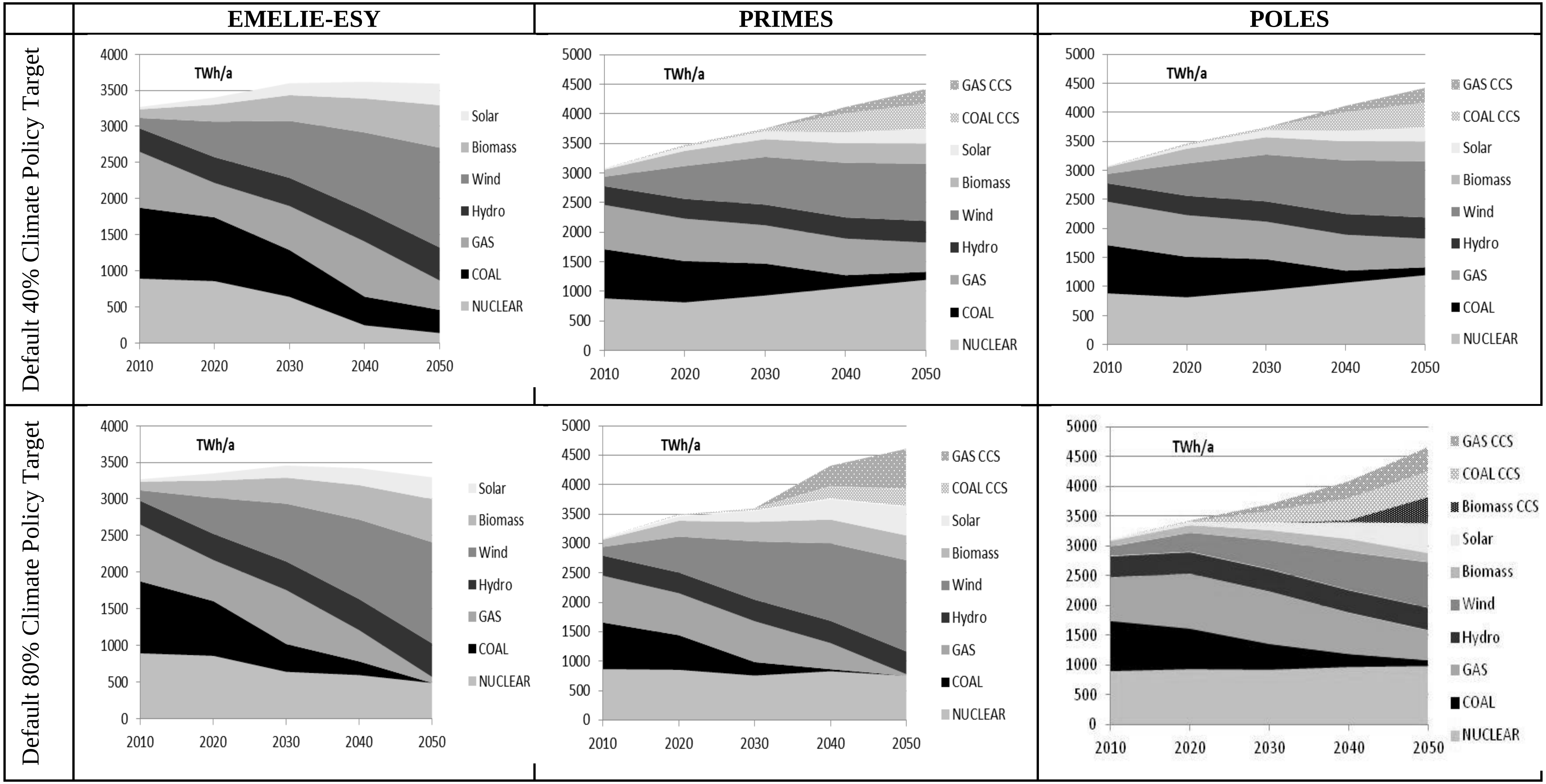

Figure 28: Power generation in the EU-27

(Source: Own compilation)

5.4.4 Power consumption and generation mix

An important determinant of the market developments and a major explanation for the observed deviations in the results of our model comparison from other peer models is the development of electricity consumption. The evolution of net power generation, i.e. final consumption including network losses, is shown in Figure 28 for the two climate policy scenarios 40%DEF and 80%DEF. Clearly, the price increases in EMELIE-ESY induce only modest increases or even a stagnant development in consumption, although reference demand grows significantly over the time horizon. Taking into account price and demand effects, we obtain a 10% increase until 2050 in scenario 40%DEF. In scenario 80%DEF we observe an increase until 2030 and a modest decrease afterwards. Quite differently, the two models used for comparison report consumption growth rates between 44 and 48% compared to the base year 2010, largely unaffected by the stringency of climate policy and the corresponding high carbon emission prices of 240-270 EUR/t in scenario 80%DEF.

Figure 28 also entails power generation by source. For the less ambitious policy scenario 40%DEF, a fading significance of nuclear power generation in the EU is demonstrated in EMELIE-ESY. Starting with a share in power generation of 27% in 2010, nuclear energy reaches 24% in 2020 and diminishes to a 4% share by 2050. The most important electricity source by 2050 is wind power, followed by biomass and hydro power. Gas power production reduces over time but replaces coal in its position as dominant fossil fuel. Whereas the 2010 reference power mix is similar in PRIMES and EMELIE-ESY, there is a significantly different evolution until 2050. The PRIMES model projects a much larger generation of conventional power plants in absolute terms. By 2050, PRIMES projects for the 40%DEF scenario all conventional power sources to exceed 50% of the EU's power production, with nuclear power as dominant source (27%). PRIMES' share of RES production of 45% by 2050 contrasts with 76% in EMELIE-ESY. This difference is mainly due to the 27% higher power consumption in PRIMES (4545 TWh/year) compared to EMELIE-ESY (3592 TWh/year).

Under the more ambitious climate policy targets of scenario 80%DEF, the role of RES gains dominant importance with a production share of 83% by 2050. The increase of RES corresponds with a reduction of nuclear power to a share of 15%, and an almost complete cutback of fossil fuel usage. Natural gas fired power production keeps merely a 2% share in power generation, whereas coal-fired power production declines completely. The absence of coal power production arises despite significant coal-fired production capacities not reaching their full lifetime by 2050. Accordingly, gas-fuelled powered plants reach only a low rate of utilization, and coal-fired power plants are not able to recover fuel and emission costs through electricity prices in the last period. Reduced competitive utilization rates and increasing emission and fuel prices are also a major obstacle for CCS technology investments as modeled in EMELIE-ESY. Since emission rates of CCS are not irrelevant under CO_2 prices of over 100 EUR/t and as high capital costs of CCS gain importance under low utilization rates, levelized costs of CCS are escalating. Under a moderate price elasticity of -0.3 the model suggests that demand is reduced rather than new CCS power plants being built.

These findings contrast with the picture drawn by the models PRIMES and POLES, where fossil fuels keep a significant share in power generation even in a world of ambitious climate policy. POLES calculates a 36% share of fossil fuelled power plants in power generation by 2050 in 80%DEF, whereas PRIMES projects a corresponding 27% share. Finally, PRIMES projects a share of nuclear energy of 20%, and POLES finds a quarter of European electricity generation produced by nuclear power in the year 2050 for scenario 80%DEF. Given increasing electricity generation, PRIMES finds a 10% decrease of nuclear power generation compared to today's production, whereas the model POLES computes an increase of about 10% with a generation of 985 TWh in 2050.

5.5 Conclusion

We have assessed the potential impacts of different climate policy regimes on electricity prices, CO_2 prices and generation capacity investment in this chapter. The results of EMELIE-ESY suggest that climate targets can be met by the power sector with only few to no investment into CCS and nuclear power plants. In fact, most scenarios propose no private investment into CCS and nuclear technology at all. The lack of new investment gives rise to high wholesale spot market prices. Price increases on the wholesale market exert downward pressure on overall power demand. Our findings contrast with the models PRIMES and POLES. Differences can be explained by significant variations of model assumptions regarding investment and generation costs for nuclear and CCS power plants. Adding to this, a key driver for differences in results is that consumption in EMELIE-ESY strongly reacts to rising wholesale prices, which result from increasing fossil fuels and CO_2 prices. PRIMES and POLES report a comparatively stable increase of electricity consumption by 2050, despite high emission prices. All in all, our findings suggest that the projected growth of RES supply can sufficiently meet electricity consumption complemented by only few capacity investments in conventional technology. This comes at the price of rising power prices which contain demand growth.

Chapter 6 – Transmission Grid Congestion Analysis

6.1 Introduction

The geographic disconnect between power generation resources and demand hubs is an important issue in the European electricity sector. Moreover, as the projected share of RES generation in the European Union is likely to triple by 2030, a temporal misalignment of demand and non-dispatchable fluctuating resources is set to become a challenge for electricity grid planners. Amongst many solutions to tackle such challenges, grid capacity expansion is often proposed to be relatively cheap but hard to implement due to problems with public acceptance. Long lead times for the planning of transmission infrastructure create the need for long planning horizons. The 3^d energy package of the European Commission mandated ENTSO-E to establish a 'Ten-Year Network Development Plan' since 2010. It is the first policy effort to bring forward coordinated long-term planning processes for European power transmission infrastructure. The German political situation is characterized by implementation of the TYNDP through the National Grid Development Plan ('Netzentwicklungsplan'). The ongoing process defines the need for additional transmission capacity within Germany up to 2032.

In the light of recent policy proposals to expand electricity grids so as to better incorporate RES into the system, different studies examine their suitability on an EU-wide scale (Troester et al. 2011; Leuthold et al. 2012; Schaber et al. 2011) and national scale (dena 2010). The project of Troester et al. (2011) makes use of a comprehensive AC load flow model to investigate transmission needs on a European level and covers the years 2030 and 2050. A peculiarity of their study is that RES generation projections are fairly optimistic with 68% and 97% of generation in 2030 and 2050, respectively. While the study is good in its geographic coverage of whole Europe, it does not allow for detailed conclusions as regards Germany since its grid representation is relatively coarse. The same holds true for Schaber et al. (2011) which focuses on European transmission grid expansions with the aim of better integrating fluctuating RES. Inner-German grid congestion and capacity expansion requirements are scrutinized in the study of dena (2010), where infrastructure needs are determined for the time range up to 2020. Although the study qualifies as the national reference study it is widely criticized for a lack of transparency (Jarass 2010) and its short temporal horizon of 2020 (Hirschhausen et al. 2010). Neither does this study allow for reproduction and scrutiny nor does it offer a place for visionary concepts of grid expansion over a long-term horizon. A long-term perspective is necessary for electricity infrastructure where excessive lead times make project planning a long-lasting endeavor. The present article is intended to address the shortcomings of the mentioned studies by applying a European-wide model with high resolution of Germany for the year 2030. Such model allows for conclusions in relation to specific line expansion projects in Germany and it also accounts for fundamental system changes likely to occur by 2030 on a European scale.

Hitherto, the research community has dealt little with applied analysis of transmission infrastructure needs. Mills et al. (2011) perform an analysis of grid integration of RES for the Western US grid. George & Banerjee (2011) do likewise for a specific Indian region. None of these studies cover the European dimension addressed specifically here in this article. Schaber et al. (2011) come close to the work performed here but focus on variability in RES provision in whole Europe while not providing detailed needs of specific transmission line expansions.

In view of the need for advanced planning, paragraph 12 of the renewed German Energy Industry Act (Federal Government 2011a) requires TSOs to establish a plan for infrastructure needs by 2012. TSOs are requested to put up a power flow model of transmission requirements for Germany based on scenarios that have been approved by the regulatory authority, the Bundesnetzagentur (BNetzA). The latest scenario draft is published in a preliminary (BNetzA 2011a) and a definitive version (TSO 2011). The article here picks up BNetzA's call for a transmission infrastructure plan and proposes solutions for the 2030 horizon with a focus on the German grid, embedded in the European context. Three scenarios are designed that describe alternative approaches to accomplish the fundamental shift in energy supply that Germany is striving for. For quantification, a variant of the state-of-the-art DC load flow model ELMOD (Leuthold et al. 2012; Weigt et al. 2010) is applied to a regionally disaggregated electricity grid under a welfare-maximizing regime. Further methodological details can be found in section 6.2, following this introduction and literature review. Section 6.3 describes input parameters. Section 6.4 presents the three scenarios of interest. Results and their discussion are outlined in sections 6.5, with section 6.6 providing the concluding remarks to the article. A more detailed analysis, including the mathematical formulation, extensive data calculations and further scenario results can be found in Boldt et al. (2012).

6.2 Methodology

The DC load flow model ELMOD is used as basis and complemented with several features as detailed hereafter. The mathematical formulation is based on an optimization problem that maximizes social welfare and it is solved in GAMS as a QCP using the CPLEX solver.

The model applies a welfare maximizing approach with a target function maximizing consumer and producer surplus (Equation 6.1). The bi-linear program is constrained by a nodal energy balance (Equation 6.5) which states that the difference between generation and demand at a specific node, net of storage, demand shifting and load in- or outflow, must be zero. A generation capacity constraint (Equation 6.6) incorporates technical generation limits of each plant type at each node and time. Production cannot be higher than the maximum net generation capacity. Net generation capacity equals gross capacity times the technology specific availability factor. Linear ramp-up constraints (Equations 6.8 and 6.9) limit the amount of capacity that can be ramped up in one time period for each technology. Ramping costs equal the product of ramped capacity and a technology-specific cost parameter.

The model includes storage and DSM as measures to flexibilize load. Constraints 6.17 and 6.18 are included stating that at each point in time at each node, storage in- and outflow cannot be greater than the corresponding storage power limit. It is assumed, over all periods, that storage power in- and outflows, corrected by the conversion efficiency factor, need to be balanced and thus their sum is equal to zero (Equation 6.21). It is further assumed that consumers have the possibility to shift their electricity consumption for a limited time range through DSM (Equations 6.22-6.24). When shedding load, consumers get compensated depending on the amount of demand that is shifted. The compensation costs are included in the objective function.

The flow on a specific line is determined by all net inputs into all adjacent nodes multiplied by their respective PTDF (Equation 6.11). These PTDF describe the flow through any individual line in dependence of the feed-in of one unit of electricity at some specified hub. They take into account that power does not necessarily flow across the shortest distance, but rather it finds its way through the grid via the path of the least resistance. This nature of power flows gives rise to so-called loop-flows in meshed grids. Implicitly, the PTDF matrix respects the Kirchhoff rules which define the relationship between electric tension and currents: At each node the sum of in- and outgoing electricity flows needs to be zero and the directed sum of the electrical potential differences (voltages) around every closed circuit (loop) equals zero.

Line flow constraints (Equations 6.11-6.16) state that the electricity flowing through a line cannot be greater than the maximum capacity of that line, in absolute terms. Since electricity can flow in both directions and the line flow can thus be positive or negative, two separate constraints are included guaranteeing that the line flow does not exceed its capacity limit on each line. By reducing the maximum line capacity below its technical potential by 20%, the n-1 security criterion is accounted for and it functions as reliability margin. A similar reasoning applies to the modeling of DC line flows. The net input into a DC line is determined by the line flows of the DC lines multiplied by their factor in the incidence matrix (Equation 6.16). As in the case of AC lines, DC lines have a certain technical power limit that cannot be exceeded at any point in time. Therefore, two constraints are included thus guaranteeing that the power flowing through a line does not exceed its technical power limit.

6.3 Application

In this section, basic input parameters and assumptions of the model are explained. The analysis considers an hourly time resolution. It is applied to four distinct representative weeks in the year 2030 and all input parameters are calibrated so as to match realistic projections for that year. It comprises 21 European countries, and disaggregates Germany into 18 zones as defined in dena (2010). Conclusions are only drawn on results for Germany although the model covers whole Europe.

The aggregation of zones results in a 41-node base model with Denmark being composed of two nodes. Note that while the model considers 234 AC lines and 35 DC lines, PTDF are used to aggregate inter-zonal lines. The calculation of PTDF is based on the ELMOD database including 3,449 European high-voltage lines at 220 and 380 kV level (Leuthold et al. 2012). Some lines are added to the existing database to reflect grid expansion projects up to 2030 as proposed in the TYNDP (details in Table 15 and Table 16). PTDF are derived from the incidence matrix and an inversion of the admittance matrix ‘B’ as outlined in Duthaler et al. (2007). Since the model application considers aggregated zones, PTDF are defined for all inter-zonal lines while all lines within a zone are left out. For nodes within a zone, there are different options for including weighting factors such as demand, gross or net generation (Smeers 2008). Weighting based on demand and generation is the best choice in theory, but not chosen here since demand and generation are endogenous. It is chosen to weigh nodes at equal rates.

6.3.1 Electricity grid

In order to model the German power market for 2030, assumptions are made about the evolution of the electricity grid, both for Germany and the rest of Europe. The section here outlines the additions that are made to the grid in place in early 2012. A number of grid expansion projects that are under consideration, in planning or in an early construction phase as of 2012 are applied exogenously to the model. German legislature, European TSO (ENTSO-E) and regional TSO indications are the basis for qualified projections of the 2030 European grid. The Energy Line Extension Act (Federal Government 2011b) prioritizes a series of national projects that have reached either late planning or early construction phases. For transmission projects at the international level the TYNDP (ENTSO-E 2010) identifies a number of projects, of which only several are picked for the application here. The upgrade of existing or construction of new lines between Germany and its neighbors provides additional power exchange capacities and increases security of supply. Since most of the projects are commissioned before 2017, they are assumed to be completed and operational by 2030. The transmission network topology in Germany and its neighboring countries are further detailed in graphs in the results section.

6.3.2 Electricity demand

According to the Federal Energy Concept on Environmentally Sound, Reliable and Affordable Energy Supply (Federal Government 2010), the German government is aiming for a demand reduction of 25% between 2008 and 2050. This amounts to approximately 16% until 2030, when applying a compound annual growth rate. It is thus assumed that there is yearly electricity demand of 463 TWh in 2030 in Germany as reference point. Note that actual demand realizations may deviate from this figure since an elastic demand function is used in the model application. On a European level, the application here uses hourly load values of the year 2010 provided by the European Network of Transmission System Operators (ENTSO-E 2011). Total German demand is allocated to the 18 model nodes inside Germany based on population data.

6.3.3 Renewable energies

The "Renewable Energy Policy Country Profiles" study of EcoFys et al. (2011) is used as a consistent basis for RES production data in Europe. The study predicts the potential of electricity generation by 2030 per technology for EU-27 countries. These projections were directly derived from the NREAP for each country in the year 2020, and reflect the official renewable energy target of each country. The 2030 forecasts also take into account existing national RES support policies as well as expert opinions, providing a higher level of detail than other comparable studies. Electricity generation data for wind, solar, hydro, wave and tidal, geothermal and biomass are converted into installed capacity using technology- and country-specific full load hour assumptions taken from the NREAP and recent projections in EcoFys et al. (2011). 2,906 TWh of RES generation are expected in the EU 27 in the year 2030. Both, on- and offshore wind, contribute a significant portion of total RES generation with 19% and 17%, respectively. Another 16% of photovoltaic generation increases the total portion of fluctuating RES to 52%.

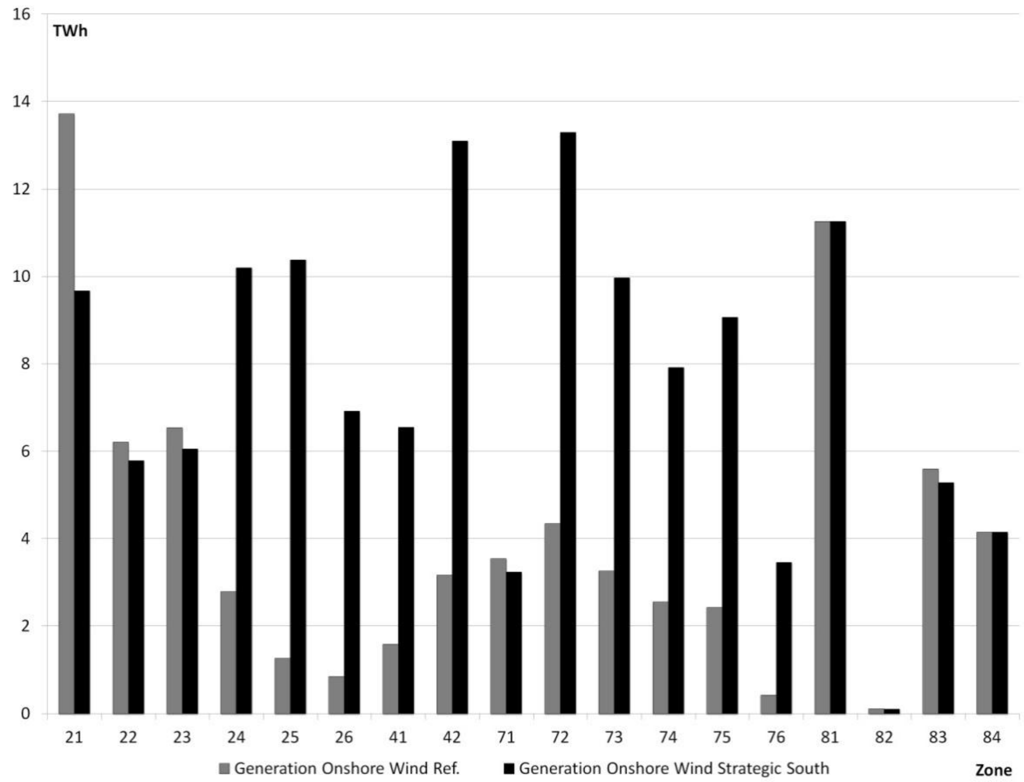

Figure 29: Onshore wind generation: Reference vs. Strategic South Scenario.
(Source: Own calculation based on EcoFys et al. (2011); Map of zones in Figure 30)

For countries with a single node representation in the model, the generation capacity is aggregated. For Germany, however, a greater level of detail is needed to guarantee accuracy. Total capacity is broken down to 18 DENA zones in a way that is plausible given geographic potential and local development plans. As there is no exact data on the regional distribution of RES generation in Germany in the EcoFys et al. (2011) study, this information is adopted from the TSO scenario pathway mentioned earlier (TSO 2011). After applying that distribution to the capacities given in the EcoFys et al. (2011) study, a regional breakdown of 2030 RES capacity in Germany is obtained (see Table 12).

Since biomass and geothermal are dispatchable technologies, their generation is controllable and does not need to be determined as time series. For the fluctuating RES, hourly feed-in-series are elaborated to model the actual generation mix over the course of a year.

- Wind power output is derived from a representative wind park as a function of wind speed. 6-hourly wind speed data is retrieved from ECMWF-ERA Interim Re-Analysis for 2005 (Dee et al. 2011) and interpolated values are derived. Data is available for a coordinate grid of 1.5 to 1.5° density, with 18 area points available for Germany. The advantage of using wind speed data over simple output time series is that offshore and onshore wind output can be disentangled and derived separately, which is done for Germany here. For other countries, their geographic center is chosen as single reference point. Note that the Interim Re-Analysis consists in a mixture of forecast and actual measures. Grid cells cover a large area and thus build average values for specific grid cells. When validating the simulation model with actual feed-in data, an R^2 of 70% can be achieved in some grid regions.

- Solar power output derivation is also based on meteorological data. Hourly irradiation values for 2005 (SoDa 2005) are used and converted into power output taking into account various losses and efficiency reductions (pre-conversion losses, inverter losses, thermal losses and conduction losses) by aggregating them in a performance ratio (Quaschning 2009). The same geographic reference points are used as for wind power derivation;

- As opposed to solar or wind power, hydro power features a fairly continuous generation profile, so there is no need for an accurate hourly generation time series. Still, seasonal variations in generation can be observed. For this reason, a generation profile by month is adopted here. Generation data from the years 2008, 2009 and 2010 is extracted from Eurostat (2011) and used as a basis for the time series calculations of hydro power.

6.3.4 Conventional electricity generation

Since the NREAP and the EcoFys et al. (2011) study do not provide any information on electricity generation from conventional resources, we revert to a study by the European Commission (EC 2010) for 2030 data on a European level. Regarding data on non EU-members, public and private studies of the respective countries were examined. A higher degree of resolution is applied to Germany for which data in the Platts (2011) database, a BNetzA (2011b) list and the original ELMOD database (Leuthold et al. 2012) are triangulated. This data is extended with projected new investments (VGB 2011) and we remove those plants which are likely to be decommissioned by 2030. For the reference scenario, it is implicitly assumed that the geographic spread of power plants does not alter until 2030. Generation costs, particularly short-term variable costs, play a crucial part in the model since they determine the sequence in which power plants are dispatched. Adding to this, ramping costs further complicate the dispatch order of power plants. Table 13 presents assumptions on marginal generation cost assuming a CO_2 certificate price of 50 EUR/tCO_2. Fluctuating RES have no fuel costs at all, and are therefore always in merit. Deep geothermal energy does not incur any fuel cost either, but its variable operation and maintenance costs of around 1.5 EUR/MWh are reflected in the marginal generation costs. Biomass plants in Europe are able to run on a variety of fuels, and their costs are aggregated at 50 EUR/MWh (BMU 2010). More details about the costs, also including ramping costs and limits can be found in the publication of Boldt et al. (2012).

DENA Zone	Geo-thermal	Hydro-power	Photo-voltaics	Wave &Tidal	Onshore Wind	Offshore Wind	Biomass	Sum
21	0.61	0.00	2.74	1.74	5.47	10.97	0.25	21.76
22	0.00	0.05	2.04	1.74	2.47	5.48	0.54	12.32
23	0.00	0.06	2.51	0.00	2.60	0.00	0.59	5.76
24	0.24	0.00	4.08	0.00	1.11	0.00	0.20	5.63
25	0.15	1.85	10.58	0.00	0.50	0.00	0.92	14.01
26	0.10	1.23	7.40	0.00	0.34	0.00	0.61	9.69
41	0.10	0.49	3.04	0.00	0.63	0.00	0.33	4.59
42	0.20	0.98	5.83	0.00	1.26	0.00	0.65	8.93
71	0.00	0.03	1.37	0.00	1.41	0.00	0.32	3.13
72	0.00	0.05	2.97	0.00	1.73	0.00	0.39	5.14
73	0.00	0.04	2.23	0.00	1.30	0.00	0.29	3.86
74	0.06	0.02	2.31	0.00	1.02	0.00	0.25	3.65
75	0.30	0.00	4.45	0.00	0.97	0.00	0.25	5.97
76	0.05	0.62	3.70	0.00	0.17	0.00	0.31	4.84
81	0.00	0.00	2.92	1.74	4.48	5.48	2.89	17.51
82	0.00	0.12	0.00	0.00	0.04	0.00	0.12	0.29
83	0.00	0.00	2.46	0.00	2.23	0.00	0.43	5.12
84	0.00	0.12	2.06	0.00	1.65	0.00	1.35	5.19
Sum	1.82	5.66	62.69	5.22	29.39	21.93	10.68	137.38

Table 12: Breakdown of RES generation capacities on Dena zones in 2030 in GW.

(Source: Own calculations based on EcoFys et al. (2011); Map of zones in Figure 30)

CHP generation is included in the analysis. Some power plants show “must run” characteristics, i.e. they generate electricity whenever they are required to produce heat. For power plants for public supply this is especially the case in winter, when district heating systems are online. In order to allocate CHP capacity to fuel type, a forecast on the share of fuel types of CHP has been made. The forecast takes into account long-term trends of CHP development and displays a significant growth of the gas and RES production share, a considerable decline in coal and oil utilization and a sharp decline of the share of other fuels, mainly due to the phase-out of nuclear energy. The share of must-run CHP and RES is not modeled separately, as renewable energies are generally considered as must run facilities. In the analysis a maximum installed capacity of 15 GW for must run non-renewable CHP plants is estimated for 2030. This maximum is reached in winter, in autumn and spring it amounts to 10 GW while in the summer it is 5 GW. The assumption represents 42% of the overall German CHP capacity if an installed capacity of 35.7 GW for the year 2030 is taken as basis (BMU 2010).

	MCoE + CO_2 [EUR/MWh_{el}]
Lignite	51.69
Hard Coal	63.69
Gas	74.91
Oil	142.84
Uranium	9.93

Table 13: Costs for fossil-based power generation including CO_2 costs.

(Source: Own depiction based on BMU (2010) and EWI et al. (2010))

6.3.5 Infrastructure cost

Infrastructure cost needs to be taken into account into the overall analysis of transmission line extensions. These costs comprise line extension cost on the one hand and generation capacity cost on the other hand.

The cost of upgrading the transmission grid depends on the length, type, capacity and terrain of the underlying transmission lines. High-voltage AC is the cheapest technology of power transmission and well established in today's power system. No large cost reductions are expected throughout the modeling horizon. Based on already built or pending project cost specifications (Troester et al. 2011), AC line extension cost is set at 400 EUR per MW and km. For a long-distance power transmission, DC lines have many advantages compared to AC lines with the same power rating. While DC lines are mainly limited by a maximum conductor temperature, the capacity of AC lines is also limited by high reactive power consumption. The DC line extension cost is set at 0.7-0.8 million EUR/km at a 3000 MW power rating with 500-600 kV voltage capacity. An AC line with the same power rating would cost 1.22 million EUR/km. It is obvious that DC lines have lower unit cost than AC lines mainly as a result of a lower number of parallel lines needed. This cost advantage is reduced by the cost for converter station costs which cost about 150,000 EUR per MW. Hence, landside DC lines pay off over long distances. All costs are annualized in order to suit to the model time horizon.

The 2030 projection of generation capacity capital cost is mainly based on values derived from the World Energy Outlook 2011 (IEA 2011a) and can be found in Boldt et al. (2012). For established generation technologies it is assumed that lower capital costs due to research and development are offset with increasing costs for materials, labor and space by 2030. For upcoming RES technologies, substantial reductions of investment costs are likely to materialize due to economies of scale, learning curves and research & development.

6.4 Scenarios

A scenario analysis is conducted that revolves around a central reference case. The variations on the Reference Scenario explore alternative possible states of the 2030 power market: while the 'Strategic South Scenario' mainly differs from the Reference Scenario in its generation structure, the 'DC Highways Scenario' focuses on alternative transmission topology. The scenarios encompass assumptions regarding demand, generation, fuel and certificate prices, grid expansions and political motives.

The Reference Scenario depicts a state of the European electricity market that is probable under the condition that additional policies support the development of RE and infrastructure development in Germany and Europe. No significant changes to current climate and energy policies are made over the course of the next 20 years. The phase-out of nuclear energy in Germany, as appointed by a 2011 amendment to the Nuclear Energy Act, will see the last nuclear power utility exit the grid in the year 2022. Newly constructed fossil-based power plants are assumed to be built at the same locations where old ones have been closed.

The Strategic South Scenario investigates an alternative to the expansion of transmission networks on a North-South axis. The research question behind the scenario is whether the strategic placement of conventional power plants close to load centers, as well as an equal distribution of RES between North and South can substitute the construction of transmission to a certain extent. The Strategic South Scenario consists of two major changes compared to the Reference Scenario: First, while in the Reference Scenario new conventional power plants are built on the location of old power plants exiting the grid, they are now being placed strategically along the metropolitan and industrialized areas of West and Southwest Germany. Especially the flexibility of additional gas turbines allows them to serve as back-up capacity for peak demand hours. Second, there is a reallocation of RES capacity from Northern Germany to the centers of high demand. The reduction of offshore wind energy capacity in the North goes with increasing RES technologies (such as PV and onshore wind) in the Southwest without affecting the total ratio of renewable versus conventional generation. Offshore wind is reduced in the Strategic South Scenario by nearly 19 GW and half of onshore and PV capacities are shifted from the North to the South. See Figure 29 for a comparison of wind capacity in the Reference and Strategic South Scenarios. It is apparent that generation in the Strategic South Scenario is explicitly larger in the zones of high demand (24, 25, 26, 41, 42, 72, 73, 74, 75 and 76) than in the Reference Scenario owing to the reallocation of resources.

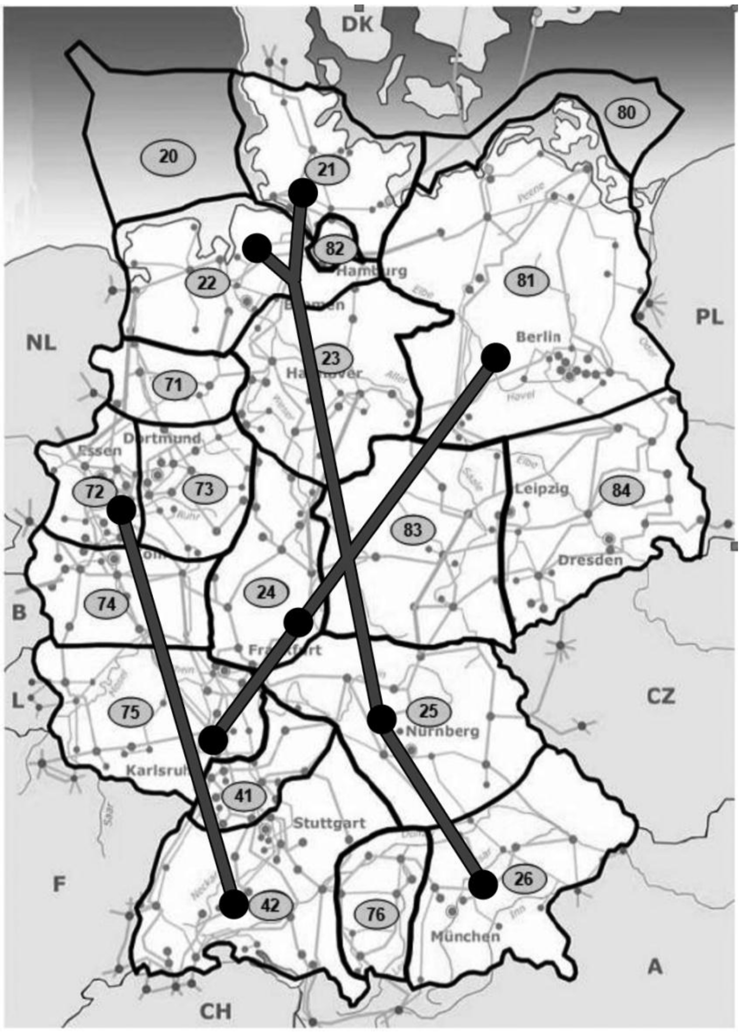

Figure 30: Proposal of DC lines. Dark circles indicate converter stations.
(Source: Own depiction based on the dena II report (2010))

The third scenario variation, the DC Highways Scenario, explores the possibilities of using state-of-the-art DC transmission technology to alleviate congestion on the high-voltage AC grid. Since projected and existing offshore wind capacity is located mainly in the North, transmission capacities on the North-South-axis are considered as efficient to relieve congestion. This discussion has gained some momentum in late 2011 when first insights into a DC-Overlay master plan have emerged. First sketches of the three DC lines' pathway were shown, see Figure 30. The lines span over 2,100km, running north to south and east to west. 50 Hertz, the transmission operator in eastern Germany, has already entered the application process for the line connecting rural Brandenburg to the densely populated Rhine-Main area. Amprion and EnBW, operating in western and southwestern Germany, are planning a 600 km line linking the Ruhrgebiet and Stuttgart, the state capital of Baden-Wuerttemberg. That region will be facing a shortage of 5 GW of reliable generation once the last of the nuclear power plants exit in 2022. TenneT, operating on a Northwest-Southeast-axis, is planning the longest of all lines, reaching over 900 km from Schleswig-Holstein to Bavaria. Its purpose will be to haul the generation of 28 GW of offshore wind across the country to a populous region that will also face substantial nuclear phase-outs. The DC Highways Scenario assumes that these projects will have reached completion and will be fully operational by 2030. The lines will start at a capacity of 1 GW with the possibility to be upgraded to 3 GW. To account for this degree of uncertainty, the three lines are modeled with 2 GW capacity. The aim of the scenario is to investigate the effects of DC overlay lines on the existing AC grid. Will the DC highways alleviate congestion on the AC grid and ease the transfer of power from north to south? All assumptions from the Reference Scenario are left intact except for the addition of the three DC lines. This methodology allows for filtering out a ceteris paribus effect of an overlay grid on transmission constraints in the AC grid.

6.5 Results and discussion

6.5.1 Four representative weeks

Four representative weeks are chosen, one for each season of the year. The ratio between RES generation from wind and solar (by far the largest contributors to RES generation in Germany) against weekly demand is chosen as the main determinant for the selection of representative weeks. The comparison of the four weeks and a more elaborate explanation of the selection process can be found in Boldt et al. (2012) together with additional information on the share of RES in total generation and on the import-export performance of Germany in the different weeks and scenarios.

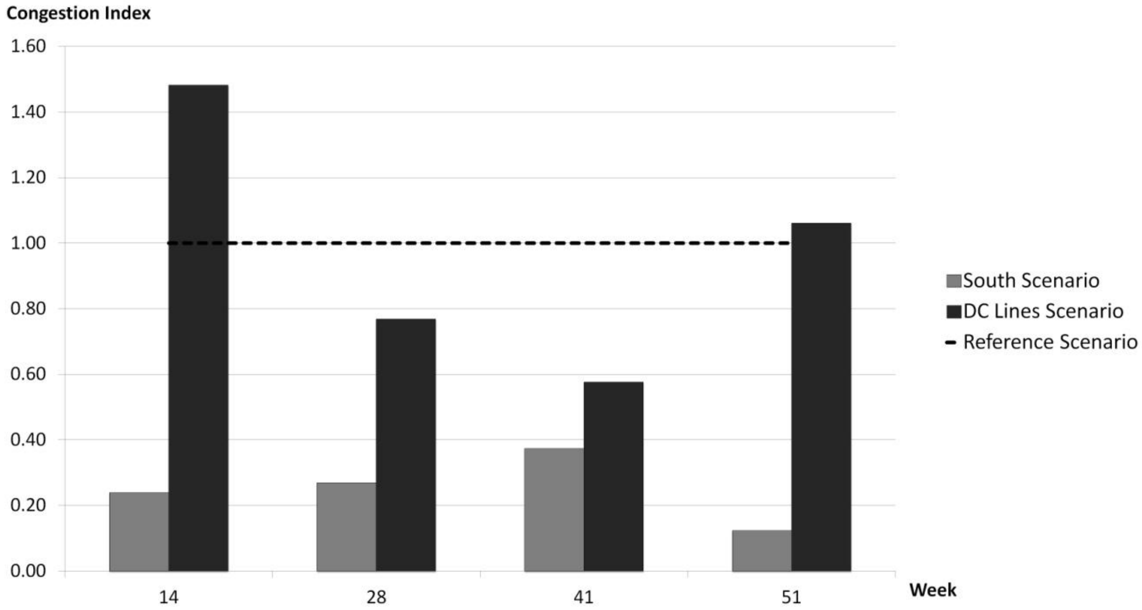

Figure 31: Congestion index for all scenarios in weeks 14, 28, 41 and 51.

(Source: Own depiction)

For an in-depth comparison of transmission grid congestion, we analyze line capacity shadow prices. Shadow prices represent the total value that the operator is able to recover in form of the so called congestion rent. Alternatively it can be interpreted as the contribution of line expansion to welfare when releasing the lines capacity constraint by 1 MW. In a transferred meaning, values indicate the urgency or priority of line expansion.

A general grid-wide weekly congestion index is used to compare congestion across scenarios. It relates the sum of shadow values of all lines in each scenario in relation to the reference scenario. This congestion index is visualized in Figure 31, the congestion index of the Strategic South and DC Lines Scenario is compared to congestion index of the Reference Scenario which is normalized to one. A value of the indicator above one represents deterioration; a lower index implies an improvement compared to the reference scenario. A drop in the congestion index may be due to the fact that lines are congested at fewer times or that the value of the congestion – the price difference between the zones – may have fallen. The chart clearly shows that the Strategic South Scenario reduces the sum of the shadow variables throughout all weeks compared to the Reference case. Its congestion index is 0.25 in average. The DC Scenario paints a different picture. It increases congestion in spring and winter, and decreases congestion in summer and autumn. The mean congestion index of the DC Scenario is 0.97, which means that on average, congestion is significantly decreased. Since the spread between the Reference index and the Strategic South index is largest for week 51, this particular week is chosen for a detailed analysis hereafter.

6.5.2 Detailed results for one exemplary week

In what follows, detailed results are outlined for week 51 of the model year. Figure 32 shows the generation portfolio of week 51 in the Reference Scenario. It shows the generation mix of the specific technologies in MW for the 168 hours of one week. While the dotted black line represents demand, the cumulated areas stand for the generation share of the respective technologies. The difference between total German demand and total German supply represents imports or exports at each hour. One can distinguish the intermittent RES, wind and PV, the controllable RES hydro, geothermal and biomass, as well as the conventional energy sources oil, gas, combined heat and power, hard coal and lignite.

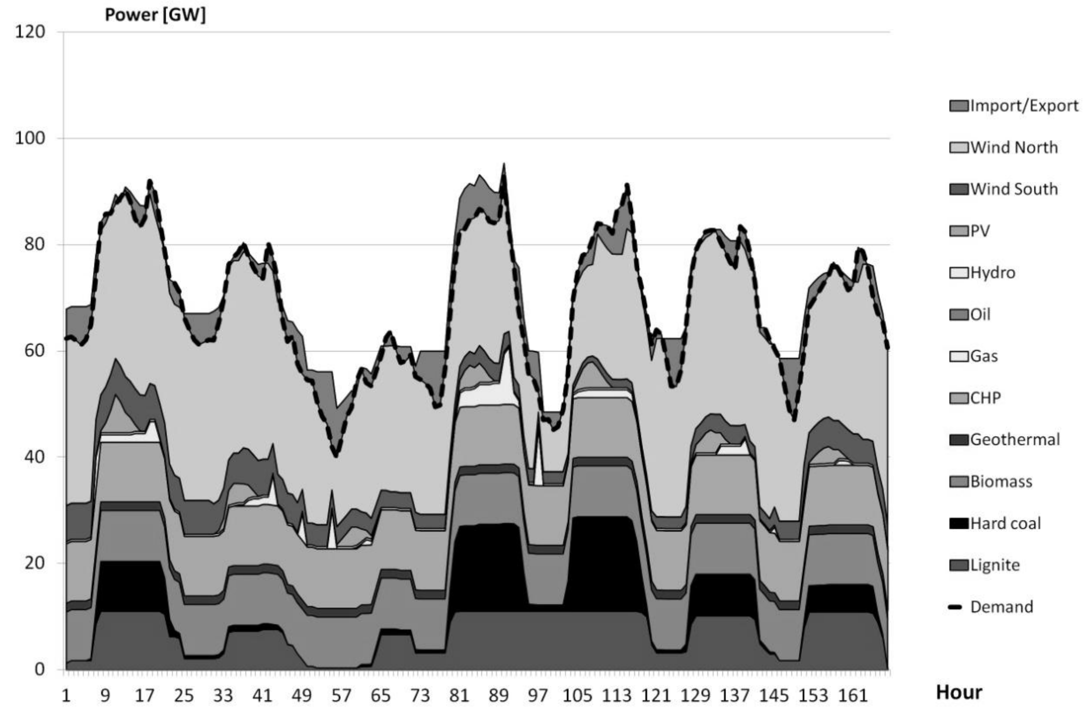

Figure 32: Generation portfolio of week 51 in the reference scenario.
(Source: Own depiction)

Concerning the generation mix, it is striking that throughout the whole week, the wind from the north of Germany, originating mainly from the offshore wind parks in the North Sea, contributes the main share of generation in Germany. There is no generation at all from oil-fired and generation of hydro power, wind from the South of Germany, geothermal, solar power and gas only represents a small fraction of total German energy supply. Electricity generation from base load technologies (lignite, hard coal, biomass and combined heat and power) accounts for an equal share of around 10 to 15%. One can observe the gas peaks which even out the uncertainties of intermittent RES. During this exemplary winter week, German production exceeds German consumption and import only occurs in a few peak demand hours. Overall, Germany exports around 3% of its electricity generation.

The generation portfolio of week 51 in the DC Highways Scenario does not change compared to the Reference Scenario owing to the similar assumptions on installed capacities. In the Strategic South Scenario there is a higher share of installed wind capacity in the south of Germany. Consequently the generation by wind power from southern Germany increases from around 5% in the Reference Scenario to more than 27% in the Strategic South Scenario. On the other hand, one can notice the decreased generation by northern wind power. Generation by the remaining technologies in each case only differs slightly, the share of fossils increases by around 5%. The RES share in the German generation portfolio remains relatively stable across all three scenarios, deviating by not more than 1%.

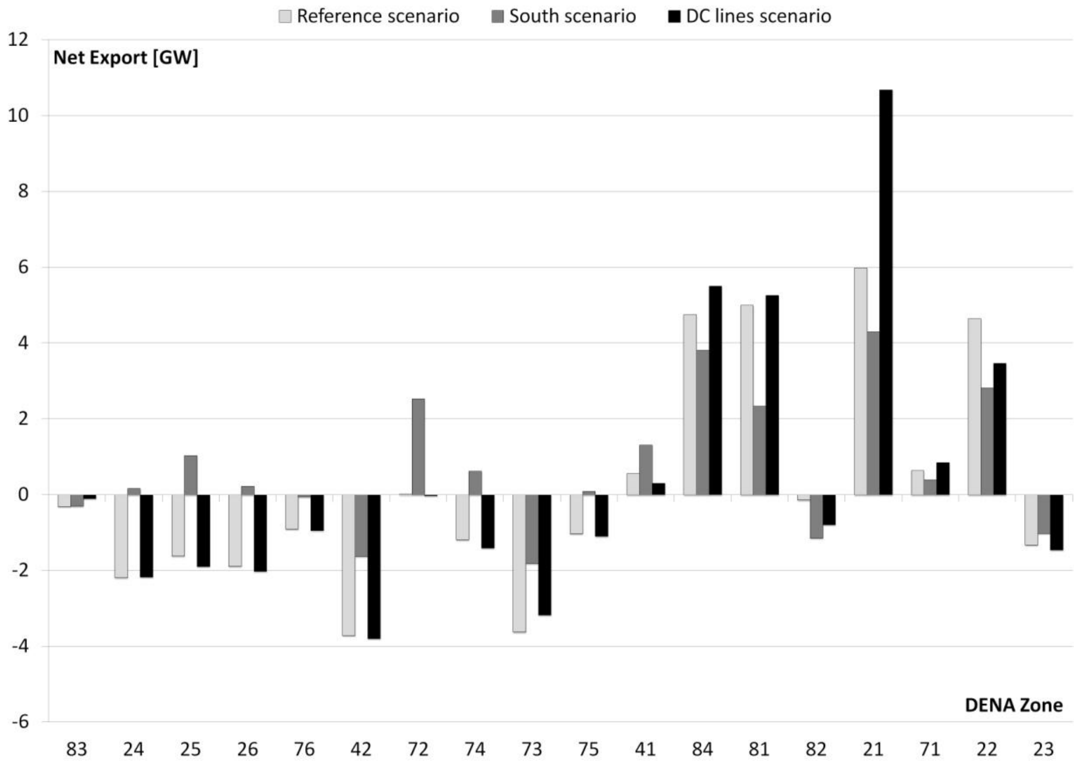

Figure 33: Net Input: Median of hourly import/export in German zones.
(Source: Own depiction)

Figure 33 shows the import/export-balance of each node in Germany. It represents the median of net electricity generation at each node over all 168 hours of week 51. The Reference Scenario clearly shows a set of exporting nodes exclusively in the very north of Germany. Sorted in descending order by their net export amount, these are: 21, 81, 84, 22, 71, 41 and 72. For the nodes 21, 22 and 81, the reason for the high amount of exported electricity lies in the large amounts of offshore wind power in the North and Baltic Sea. As wind is under a must-run condition (marginal cost of zero) and exceeds local demand, the zones become net exporters in weeks with significant wind, such as week 51. The other four exporting nodes have a high installed capacity of onshore wind and good wind conditions over the whole year. The major importing zones of the Reference Scenario are 73, 42, 24 and 26, all located in Germany's west and south. This is caused by the loss of large shares of installed capacity (nuclear phase-out) and a strong demand.

The DC Highways Scenario brings little structural change to the national export and import patterns observed in the Reference Scenario, except in the Northern German zone 21. Here, a major increase of electricity export to other zones is made possible through new DC transmission capacity to the Southern load centers. A side effect is that nodal prices increase in Northern exporting zones and they align with formerly high southern prices. All in all, the nation-wide export to neighboring countries increases by 4%.

In the Strategic South Scenario, the national import-export pattern is fundamentally shifted. First of all, the inner-German disequilibrium between northern exporters and southern importers tends towards a balance. All nodes experiencing a major decrease in imported electricity are located in the south and west of Germany and all former main exporters experiencing a decline of net exports are located in the north of Germany. A second observation is that there is a clear shift towards more export from Germany into neighboring countries. As a matter of fact, Germany turns from a net moderate importing (around 3% of production) in the Reference Scenario to a major net exporting country (around 17% of production). We conclude that the strategic placement of installed capacity to demand regions brings relief to the connection between exporting and importing zones and improves the overall German export ratio.

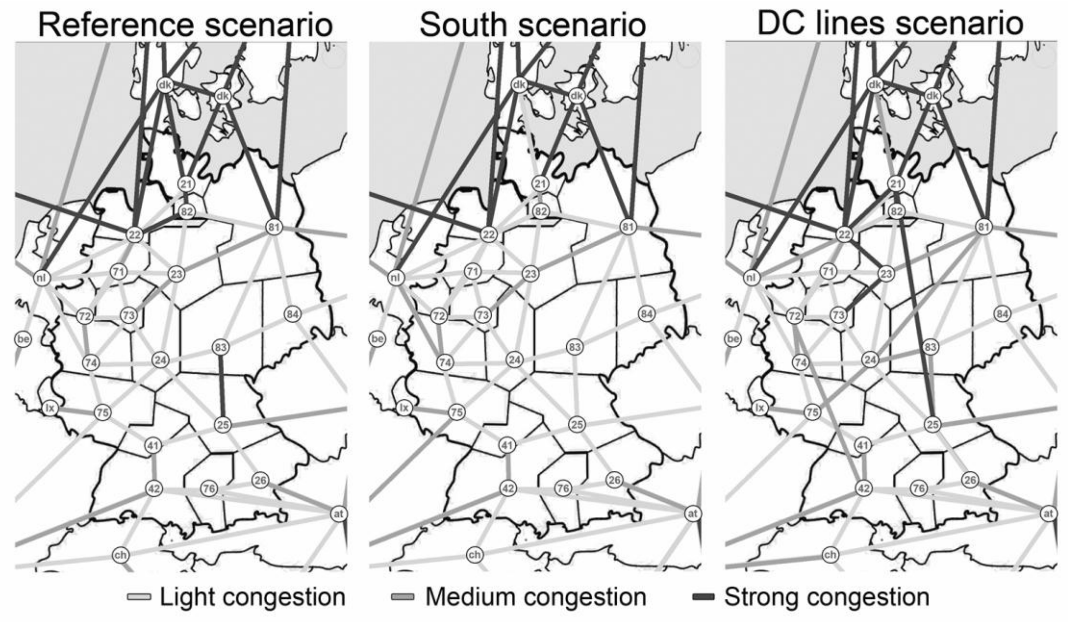

Figure 34: Line congestion in three scenarios measured in terms of shadow value.

(Source: Own depiction)

In what follows, congestion patterns in week 51 are scrutinized in detail in order to point out changes across the different scenarios. Subject of investigation is the congestion status of the German AC Grid, which is evaluated by the individual shadow variables of the lines.

Figure 34 illustrates the congestions of each line in the three scenarios. Congestion is categorized in three classes depending on its severity, as explained in the legend. As anticipated there is strong congestion on the interconnectors to northern Europe and on the inner-German line called "Rennsteig" (line from node 25 to node 83), which is an important north-south connector in development. These results show that there will be a need for further grid extension in the reference case to transport all the offshore and onshore wind energy from northern Germany to southern Germany and to the rest of Europe.

Most of the congestion in the northwest is alleviated in the South Scenario as the congestion index falls significantly for almost all inner-German lines and interconnectors. Especially the north-south connectors and interconnectors to northern Europe, which were congested in the Reference Scenario, show a strong improvement. We conclude that grid capacity planning and generation capacity planning are intertwined problems which should ideally be coordinated in conjunction so as to reduce cost from a societal perspective.

A key finding of the DC Highways Scenario is that inner-German congestion is not necessarily relieved by building DC lines across the country. Even though a DC-grid enforcement reduces the congestion of some interconnectors and parallel running north-south lines, it goes along with higher congestion on other inner-German lines. The main reason for the latter is that additional congestion occurs at the starting and ending points of the DC lines as the existing AC infrastructure is not yet equipped for spreading the electricity through those "spokes" to the different consumer centers. It can be concluded that the planning of DC lines is not sufficient in itself, but needs to go hand in hand with a surrounding AC grid planning in destination zones.

6.5.3 Welfare analysis

The analysis of the impact on welfare contains results calculated from the model as well as specific costs incurred to build the infrastructure available in the scenarios. For the Reference Scenario no additional costs are added since this scenario is business-as-usual. However, for the DC Highways Scenario costs for the expansion of the DC grid are added based on cost assumptions explained previously. Moreover, infrastructure costs occur in the Strategic South Scenario due to shifts in the newly built capacity in southern Germany. It is obvious that these infrastructure costs should be taken into account for a welfare analysis.

	Reference [m€]	Strategic South [m€]	DC Highway [m€]
Welfare per month	13,422	13,545	13,537
Infrastructure cost per month	-	-9	54
Net welfare per month	13,422	13,553	13,483
Change in %	-	+ 0.98%	+ 0.45%

Table 14: Overview welfare effects summed over four representative weeks.
(Source: Own calculation based on EcoFys et al. (2011))

Based on the investment costs for renewable energy, these changes lead to lower costs in total. The reason is that the investment costs for onshore wind power plants are notably lower than the costs for offshore wind power plants. In total 834 million EUR can be saved through the shift of capacity in the Strategic South scenario. This translates into 8.6 million EUR monthly when considering different physical lifetimes for technologies (PV: 25 years; on- and offshore wind and wave and tidal: 20 years).

For the DC Highways Scenario, expansion costs with a total amount of 9 billion EUR are assumed. This value includes variable grid costs and fixed costs for converter stations at nine nodes (both referring to a line capacity of 2 GW). Since these costs are the investment costs for a grid with an operational life of 40 years, an annuity with an interest rate of 7% is used, analogue to the interest rate determined by the federal network agency BNetzA. The calculation yields to annual costs of 675 million EUR and to monthly costs of 54.5 million EUR.

In conclusion, we observe overall positive welfare effects of DC lines and a strategic placement of generation capacity close to demand centers, even after deduction of infrastructure costs, as seen in Table 14. Consequently, the placement of additional generation capacities into demand centers is found to be effective in reducing congestion. Likewise, DC lines as proposed in this study are a sensible and cost-effective approach to alleviating transmission grid congestion. The positive effect on welfare is higher in the Strategic South Scenario, certainly due to the cost reductions evoked by the major changes in installed capacity. However, also the DC Highways Scenario generates a higher welfare without any changes in the capacity. Hence, congestion relief appears to be the key driver for the improvement through new lines. However, both scenarios show that there still remains further need for grid upgrades in the ordinary AC grid. Implementing DC lines and placing capacities in the South are not sufficient measures to fully satisfy the grid requirements imposed by the 2030 energy system. The analysis points to the need for grid expansion beyond what is currently planned in the TYNDP context.

6.6 Conclusions

The results presented above indicate that the German AC/DC grid as planned in the TYNDP is likely to feature high line congestion and it is thus not capable of fully integrating the amount of renewable energy to the extent that welfare maximization would suggest desirable. Unless transmission lines are reinforced, a welfare-optimizing dispatch of generation for Germany in a European context is thus unlikely to take place.

Throughout all three scenarios, we observe congestion centers in the northwest of Germany which extend towards the south, as well as at the interconnectors between Germany and its northern neighbors. The connections to Poland, the Czech Republic and the Netherlands are also continuously operating at capacity limit but with a lower possible contribution to welfare optimization. As a consequence, RES power originating from the northern offshore generation centers (DENA zones 21 & 22, Great Britain) does not reach German and foreign load centers in its entirety.

The modifications made in the DC Highway and Strategic South Scenario create an alleviating effect on congestion. The Strategic South Scenario shows the best results, indicating that an even distribution of generation across the country does provide an alternative to massive transmission investments. However, given that national policy is ultimately aiming for 100% of RES generation in 2050, the reinforcement of existing and the construction of new lines seem inevitable at this point. Within the DC Highways Scenario, the AC congestion actually worsens after the introduction of the DC lines. While the north-south axis is relieved, congestion problems are transferred to starting and destination hubs and prove that there is still a need for reinforcements of the AC lines.

6.7 Appendix

The objective function maximizes social welfare

$$\max W = \left[\sum_t \left(\begin{array}{c} \left(q_{area}(t) - Cost_{var}(t)\right) \\ -\sum_{s,n} g_{up}(t,s,n) \cdot Cost_{ramp}(s) \\ -\sum_n Cost_{DSM}(s) \cdot DSM_{OUT\,l,m,h}(t,n) \end{array} \right) \right] \tag{6.1}$$

where the demand function may be described as

$$q_{area}(t) = \sum_n a(t,n) \cdot q(t,n) + 0.5 \cdot m(t,n) \cdot q(t,n)^2 \tag{6.2}$$

with the slope

$$m(t,n) = \frac{p_{ref}(t)}{\varepsilon \cdot \lambda \cdot q_{ref}(t)} \tag{6.3}$$

and the intercept

$$a(t,n) = p_{ref}(t) - \lambda \cdot q_{ref}(t) \cdot m(t,n). \tag{6.4}$$

When solving Eq. (7.1) several energy balance constraints have to be accounted for. The nodal balance constraint has to be true for any node at any point in time

$$\begin{aligned} \sum_s G(n,s,t) &+ wind_{max}(t,n) + hydro_{max}(t,n) + pv_{max}(t,n) \\ &+ \sum_{st} \left(S_{IN}(st,n,t) - S_{OUT}(st,n,t)\right) + AC_{netinput}(t,n) \\ &+ DC_{netinput}(t,n) + DSM_{OUT\,l,m,h}(t,n) - DSM_{IN\,l,m,h}(t,n) \\ &- q(t,n) = 0 \end{aligned} \tag{6.5}$$

as well as the generation capacity constraint

$$G(t,s,n) \leq rev(s) \cdot G_{max}(n,s), \tag{6.6}$$

the cost function

$$Cost_{var}(t) = \sum_{s,n} G(t,s,n) \cdot c(s), \tag{6.7}$$

the ramping constraints

$$Lim_{ramp} \geq \; G(t,s,n) - \; G(t-1,s,n), \tag{6.8}$$

$$Lim_{ramp} = \; Perc_{ramp} \cdot \; G_{max}(n,s), \tag{6.9}$$

and the definition of the ramping variable

$$g_{up}(t,s,n) \geq \; G(t,s,n) - \; G(t-1,s,n). \tag{6.10}$$

As we model a power market with both AC and DC flows, we account for AC flow constraints

$$AC_{lineflow}(l,t) - \sum_{n} ptdf(l,n) \cdot AC_{netinput}(t,n) = 0, \tag{6.11}$$

$$-AC_{p_{max}}(l) \leq AC_{lineflow}(l,t) \leq \; AC_{p_{max}}(l), \tag{6.12}$$

$$\sum_{n} AC_{netinput}(t,n) = 0 \tag{6.13}$$

as well as for DC load flow constraints

$$\sum_{dcl} DC_{lineflow}(dcl,t) = 0, \tag{6.14}$$

$$-DC_{p_{max}}(dcl) \leq DC_{lineflow}(l,t) \leq \; DC_{p_{max}}(dcl) \tag{6.15}$$

$$DC_{netinput}(t,n) - \sum_{n} DC_{netinput}(t,n) \cdot DC_{incidence}(dcl,n) = 0. \tag{6.16}$$

The n-1 security criterion is approximated by reducing the capacity of each AC line by a transmission reliability margin (20%). Note that the model neglects transmission losses. This is done to keep the model tractable and to omit non-linear elements where possible.

Regarding the implementation of storage technologies, the model considers storage power limits

$$S_{IN}(st,n,t) - S_{IN_{max}}(st,n,t) \leq 0, \tag{6.17}$$

$$S_{OUT}(st,n,t) - S_{OUT_{max}}(st,n,t) \leq 0 \tag{6.18}$$

and storage capacity limits

$$\begin{aligned} S_{LEVEL}(st,n,t) \\ = \Big(S_{LEVEL}(st,n,t-1) - \; S_{OUT}(st,n,t) + \; S_{IN}(st,n,t) \cdot \; S_{eff}(st)\Big). \end{aligned} \tag{6.19}$$

We use the formulation of a storage state variable which indicates the state-of-charge.

$$S_{cap_{max}}(st,n) \geq S_{LEVEL}(st,n,t) \tag{6.20}$$

An overall balance guarantees that the storage device left at the same state-of-charge as in the beginning.

$$\sum_{t} S_{IN}(st,n,t) \cdot S_{eff}(st) - S_{OUT}(st,n,t) = 0 \tag{6.21}$$

DSM constraints for different cost segments restrict the amount of shiftable load

$$DSM_{IN\,l,m,h}(t,n) - DSM_{MAX\,l,m,h}(t,n) \leq 0, \tag{6.22}$$

$$DSM_{OUT\,l,m,h}(t,n) - DSM_{MAX\,l,m,h}(t,n) \leq 0 \tag{6.23}$$

A balance condition ensures that load is shifted only within a certain time frame t-1 and t+1

$$DSM_{IN\,l,m,h}(t-1,n) - DSM_{OUT_{\,l,m,h}}(t+1,n) = 0. \tag{6.24}$$

All parameters and variables are detailed in the Table of Appendix 7.8.

Domestic		
From	To	Type
Ganderkesee	St. Hülfe	380kV
Vieselbach	Altenfeld	380kV
Altenfeld	Redwitz	380kV
Diele	Niederrhein	380kV
Wahle	Mecklar	380kV
Hamburg	Dollern	380kV
Wehrendorf	Gütersloh	380kV
Kruckel	Dauersberg	380kV

International		
From	To	Type
Aldeadávila (ES)	Lagoaça (PT)	new 400 kV line
Guillena (ES)	Tavira (PT)	new 400 kV line
Moulaine (FR)	Aubange (BE)	new 220 kV line
Bressanone (IT)	Innsbruck (AT)	new 400 kV line
Okroglo (SI)	Udine (IT)	new 400 kV line
Lavorgo (CH)	Morbegno (IT)	new 400 kV line
Cornier (FR)	Piossasco (IT)	new 400 kV line
Hurva/Hallsberg (SE)	Barkeryd (NO)	new 400 kV line
St. Peter (AT)	Isar (DE)	new 380 kV
Krajnik (PL)	Neuenhagen (DE)	new 400 kV line
Plewiska (PL)	Eisenhüttenstadt (DE)	upgrade to 400 kV
Doetinchem (NL)	Niederrhein (DE)	new 400 kV line

Table 15: Additions to the AC grid of 2030 versus today.

(Source: Based on ENTSO-E (2010))

International		
Name	From - To	Capacity [MW]
NORNED	Netherlands - Norway	700
Baltic Cable	21 - Sweden	600
Kontek	81 - Denmark East	600
Kontiskan 2	Denmark West - Sweden	300
Skagerrak 1+2	Denmark West - Norway	500
SwePol	Poland - Sweden	600
IFA	Great Britain - France	2000
BirtNed	Great Britain - Netherlands	1000
Norwegian Interconnector	Great Britain - Norway	1400
Storebaelt	Denmark West - Denmark East	600
Nord.Link	22 - Norway	1400
NORNED2	Netherlands - Norway	700
NordSüd1	21 - 25	2000
NordSüd2	25 - 26	2000
NordSüd3	21 - 22	2000
OstWest1	81 - 24	2000
OstWest2	24 - 75	2000
Südwest	72 - 42	2000
Skagerrak 3	Denmark West - Norway	440
Skagerrak 4	Denmark West - Norway	700
East-West-Energy Bridge (Siemens)	81 - Poland	500
COBRA	Denmark West - Netherlands	700
NEMO	Great Britain - Belgium	1000
IFA 2	Great Britain - France	1000
Gunfleet Sands1	Great Britain - Netherlands	1000
Gunfleet Sands2	Great Britain - Belgium	1000
Noth Sea Plattforms UK - Dollert (Emden)	Great Britain - 22	1000
Noth Sea Plattforms - Danmark	22 - Denmark West	2000
SwePol 2	Poland - Sweden	600
Balltic Cable 2	21 - Sweden	600
Baltic Sea Plattforms - Sweden	81 - Sweden	600
Baltic Sea Plattforms - Danmark	81 - Denmark East	600
TYNDP - Sta. Llogaia (ES) - Baixas (FR)	Spain - France	2000
TYNDP - Grande Ile (FR) Piossasco (IT)	France - Italy	1000
TYNDP - Candia (IT) - Konjsko (HR)	Croatia - Italy	1000

Table 16: Additions to the DC grid of 2030 versus today.

(Source: Own compilation based on Le Tene Maps (2011))

Chapter 7 – Interactions between Generation Capacity Expansion and Grid Development

7.1 Introduction

While the expansion and coordination of power transmission capacities remains an important focus of network planning, stakeholders are increasingly concerned with the future composition of the power generation mix as a whole and its interdependence with transmission grid planning. The optimal combination of different types of plants that accounts for the specific characteristics of an energy system dominated by RES has yet to be determined.

Most stakeholders agree that securing RES integration calls for the expansion of power plant capacities as back-up reserves in addition to the expansion of transmission capacities (ENTSO-E 2009). An important and unanswered question, though, is how this additional capacity will be composed and its optimal geographical distribution. Numerous studies have – at least in part – dealt with the optimal amount of generation capacity expansion but they have shortcomings in terms of infrastructure representation. In particular, the available literature gives no or only vague information concerning transmission grids, the supply of reserve capacities and the geographical allocation of plants. In this analysis we therefore propose a more detailed approach on interactions between network planning and power plant investment. We apply a welfare maximizing model for Germany and Central Europe in order to determine how many back-up power plants of which specific type will be needed in the medium term, given the grid structure of 2030. Our model also provides details on the optimal geographical distribution of the future generation system and its impact on grid congestion. This information is of great importance when allocating new back-up plants within the energy grid. As benchmarks for the future expansion of RES generation have already been set in Europe, we take a special focus on the expansion of conventional capacities. Our aim is to investigate which conventional energy resource best fits into the future grid dominated by RES, how many additional plants of this type are needed to provide energy security at reasonable costs and where they should be best placed. Furthermore, we investigate how the different flexibility options (i.e. storage, DSM and back-up power plants) affect congestion patterns in the electricity grid and what that means for the recently proposed grid expansion projects in Germany (TSO 2012).

The rest of the chapter is organized as follows. Section 7.2 gives a short overview on the current literature on energy network planning and capacity expansion in Germany and Europe. Section 7.3 briefly outlines the model applied in this study while Section 7.4 provides details on the data used. Scenarios are outlined in Section 7.5. Results are presented in Section 7.6 and some conclusions from our findings as well as a summary can be found in Section 7.7.

7.2 Literature review

Numerous studies deal with the future development of conventional generation capacity in the German energy grid and – using various types of models – their conclusions and methodical disadvantages differ significantly. The majority of studies suggest that even with a continuous increase of RES generation capacity, there will still be a need for the installation of additional conventional power plants.

In a detailed discussion on future capacity adequacy, Maurer et al. (2012) claim that there is a need for at least 19 GW additional generation capacity for Germany. The analysis is based on a model that adopts a national ‘autarky’ view of system adequacy and no indication is given to the expansion need under an integrated European market regime. As many other studies, Maurer et al. (2012) omit the importance and benefits of integration of spatially separated electrical systems with different generation mixes, as pointed out by Scorah et al. (2012).

The Kurzanalyse Kraftwerksplanung (dena 2008) optimizes power plant expansion under exogenous demand but it is not specific on their geographic allocation. The analysis considers an increasing need for reserve energy (from 0.84 GW positive and 0.6 GW negative in 2003 to 3.2 GW positive and 2.1 GW negative in 2015) and predicts a need for additional conventional plant capacity (coal and gas) of 10 to 14.2 GW in 2020. Another study by dena (2010) delivers more differentiated conclusions. Using the DIME model - in which power demand is again determined exogenously - it predicts that the capacity of all conventional power plants will decrease except for lignite-fired plants which is supposed to increase from 20.4 GW in 2005 to 24.3 GW in 2020. According to the authors, even though gas-fired power plants might provide necessary flexibility, they would be replaced by modern and more efficient new coal-fired plants due to high gas prices. However, even though the study builds on a strong data basis regarding infrastructure, it neither specifically optimizes the power plant fleet nor does it go beyond a 2020 horizon.

The Potsdam Institute for Climate Impact Research (Knopf et al. 2011) uses the model MICOES to determine a need for increased fossil fueled power generation capacity by 8 GW in addition to already planned power plants. It does not model plant construction as endogenous variable though. The Potsdam Institute also uses LIMES (Haller et al. 2012), a simultaneous grid and generation expansion model which minimizes power system costs. Here, power demand is exogenously determined through existing projections and capacity expansion is endogenous. The grid representation in the model is aggregated showing nation-by-nation NTC values as well as employing a piping model rather than a power flow model. In a transmission expansion scenario the authors consider Germany to use large energy imports from Northern Europe to balance demand fluctuations and thus become a net importer of energy. Nevertheless, the LIMES model results project massive gas power plant expansion for Germany in the order of 20 – 30 GW by 2030. These values take into account projected transmission grid expansion and, thus, improved European market integration.

On the European level, the Energy Roadmap 2050 (EC 2011) offers a comprehensive impact assessment of several policy scenarios. It uses PRIMES and a set of complementing models defining macro-economic developments in order to determine the market equilibrium for energy demand and supply. Due to intermittency of RES production, additional investment in conventional capacity is predicted to be necessary with the amount depending on which of the outlined policy pathways are chosen. Installed gas-fired power capacity is supposed to increase across all policy scenarios while coal-fired energy capacity decreases in most scenarios. Other studies point into the same direction. The World Energy Outlook (IEA 2011d) takes a global perspective using the World Energy Model and predicts additional installation of conventional energy capacity in Europe from 2011 to 2035 mainly in the field of gas-fired plants (139 GW) and coal-fired plants (67 GW). EWI (2012) uses the DIMENSION simulation model for the European electricity market and find that gas-fueled generation capacity will almost double to 55 GW in 2030 while investment in other conventional resources declines. Unfortunately, neither of these studies gives information on the preferred allocation of power plants within Europe or Germany.

Some studies specifically consider uncertainty in energy supply from fluctuating RES. Nagl et al. (2012) develop a stochastic combined investment and dispatch model with uncertainty in the feed-in of wind and solar energy sources and apply it to the European electricity system. The objective of the piping model formulated as LP is to minimize total system costs. It thus adopts a system perspective and takes into account correlations between solar and wind feed-in. Capacities of conventional power plants are projected to decrease for coal and nuclear power and increase for gas power plants.

Only few studies provide implications on the optimal geographic distribution of power plants in Germany. One of these is presented by Dietrich et al. (2010) who analyze power plant placing in Germany with ELMOD under nodal pricing and in a system cost minimization approach with 12 time slots included at the dispatch stage. In a welfare case where a benevolent planner is assumed to minimize costs, power plants are mostly placed in the south-western part of the country and on the northern coast line when taking a national perspective. However, when allowing for multinational planning, the study sees much more capacity investment in Lower Saxony and North Rhine-Westphalia, especially close to the Benelux border in order to relieve cross-border congestion.

In the models currently used to predict developments in composition and distribution of the power plant fleet in Germany, three general disadvantages arise from the preceding overview. First, most applications minimize costs rather than maximizing welfare which could give detailed insight into preferable energy policies by setting a benchmark. Second, none of these models considers demand as price-sensitive and partly controllable input factor, although DSM tools gain importance in electricity markets. In a market economy, the correct depiction of demand should be given more consideration. Third, no study gives very detailed implications on the desirable allocation of conventional power plants in Germany. Bearing in mind the significant problems of transmission, this is a crucial question to be answered. All three gaps could be filled by a model proposed in this chapter. An additional value of this work stems from our novel consideration of German electricity grid expansion plans outlined in the TSO proposal of June 2012 (TSO 2012). Most previously mentioned studies omit the interaction between transmission grid planning and power plant placing. We explicitly model the interaction between transmission projects flexible alternatives (i.e. Storage, DSM, back-up power plants).

7.3 Model formulation

Our electricity market model is formulated as QCP. It maximizes a social welfare function which is subject to several constraints and facing a price elastic demand function. The model is an evolution derived from Boldt et al. (2012) which in turn uses the ELMOD model developed by Leuthold et al. (2012). This DC load flow approach is superior to simple piping models (EC 2011; Haller 2012) because it accounts for loop flows, a peculiar characteristic of electricity flows. The lossless DC load flow model here is formulated on the basis of PTDF, which indicate the amount of power flow at each line in dependence of power injection at some specified hub. DC lines are treated separately from AC lines as they are assumed to be point-to-point connections not causing loop flows.

The model also includes various storage technologies. It implements a stepwise cost function for load management (DSM) in order to realistically represent this feature of a flexible energy market. A restriction is imposed so that load can be shifted only within a certain time frame.

A detailed description of the model used is given in Boldt et al. (2012) so we will only briefly recapitulate it here. In order to maximize social welfare we solve the following problem

$$\max W = \sum_t \left(q_{area}(t) - Cost_{var}(t)\right) - \sum_{t,s,n} g_{up}(t,s,n) \cdot Cost_{ramp}(s) - \sum_{t,n} Cost_{DSM}(s) \cdot DSM_{OUT\,l,m,h}(t,n) - \sum_{s,n} I(s,n) \cdot Cost_{INVEST}(s,n) \tag{7.1}$$

where the demand function may be described as

$$q_{area}(t) = \sum_n a(t,n) \cdot q(t,n) + 0.5 \cdot m(t,n) \cdot q(t,n)^2 \tag{7.2}$$

with the slope

$$m(t,n) = \frac{p_{ref}(t)}{\varepsilon \cdot \lambda \cdot q_{ref}(t)} \tag{7.3}$$

and the intercept

$$a(t,n) = p_{ref}(t) - \lambda \cdot q_{ref}(t) \cdot m(t,n). \tag{7.4}$$

When solving Eq. (7.1) several energy balance constraints have to be accounted for. The nodal balance constraint has to be true for any node at any point in time

$$\sum_s G(n,s,t) + wind_{max}(t,n) + hydro_{max}(t,n) + pv_{max}(t,n) + \sum_{st} \left(S_{IN}(st,n,t) - S_{OUT}(st,n,t)\right) + AC_{netinput}(t,n) + DC_{netinput}(t,n) + DSM_{OUT\,l,m,h}(t,n) - DSM_{IN\,l,m,h}(t,n) - q(t,n) = 0 \tag{7.5}$$

as well as the generation capacity constraint

$$G(t,s,n) \leq rev(s) \cdot \left(G_{max}(n,s) + I(s,n)\right), \tag{7.6}$$

the cost function

$$Cost_{var}(t) = \sum_{s,n} G(t,s,n) \cdot c(s), \tag{7.7}$$

the ramping constraints

$$Lim_{ramp} \geq G(t,s,n) - G(t-1,s,n), \tag{7.8}$$

$$Lim_{ramp} = Perc_{ramp} \cdot \left(G_{max}(n,s) + I(s,n)\right), \tag{7.9}$$

and the definition of the ramping variable

$$g_{up}(t,s,n) \geq \; G(t,s,n) - \; G(t-1,s,n). \tag{7.10}$$

As we model a power market with both AC and DC flows, we account for AC flow constraints

$$AC_{lineflow}(l,t) - \sum_{n} ptdf(l,n) \cdot AC_{netinput}(t,n) = 0, \tag{7.11}$$

$$-AC_{p_{max}}(l) \leq AC_{lineflow}(l,t) \leq \; AC_{p_{max}}(l), \tag{7.12}$$

$$\sum_{n} AC_{netinput}(t,n) = 0 \tag{7.13}$$

as well as for DC load flow constraints

$$\sum_{dcl} DC_{lineflow}(dcl,t) = 0, \tag{7.14}$$

$$-DC_{p_{max}}(dcl) \leq DC_{lineflow}(l,t) \leq \; DC_{p_{max}}(dcl) \tag{7.15}$$

$$DC_{netinput}(t,n) - \sum_{n} DC_{netinput}(t,n) \cdot DC_{incidence}(dcl,n) = 0. \tag{7.16}$$

The “n-1” security criterion is approximated by reducing the capacity of each AC line by a transmission reliability margin (20%). Note that the model neglects transmission losses. This is done to keep the model tractable and to omit non-linear elements where possible.

Regarding the implementation of storage technologies, the model considers storage power limits

$$S_{IN}(st,n,t) - S_{IN_{max}}(st,n,t) \leq 0, \tag{7.17}$$

$$S_{OUT}(st,n,t) - S_{OUT_{max}}(st,n,t) \leq 0 \tag{7.18}$$

and storage capacity limits

$$\begin{aligned} &S_{LEVEL}(st,n,t) \\ &\quad = \Big(S_{LEVEL}(st,n,t-1) - \; S_{OUT}(st,n,t) + \; S_{IN}(st,n,t) \cdot \; S_{eff}(st)\Big). \end{aligned} \tag{7.19}$$

We use the formulation of a storage state variable which indicates the state-of-charge.

$$S_{cap_{max}}(st,n) \; \geq S_{LEVEL}(st,n,t) \tag{7.20}$$

An overall balance guarantees that the storage device left at the same state-of-charge as in the beginning.

$$\sum_{t} S_{IN}(st,n,t) \cdot S_{eff}(st) - S_{OUT}(st,n,t) = 0 \tag{7.21}$$

DSM constraints for different cost segments restrict the amount of shiftable load

$$DSM_{IN\,l,m,h}(t,n) - DSM_{MAX\,l,m,h}(t,n) \leq 0, \tag{7.22}$$

$$DSM_{OUT\,l,m,h}(t,n) - DSM_{MAX\,l,m,h}(t,n) \leq 0 \tag{7.23}$$

A balance condition ensures that load is shifted only within a certain time frame t-1 and t+1

$$DSM_{IN\,l,m,h}(t-1,n) - DSM_{OUT\,l,m,h}(t+1,n) = 0. \tag{7.24}$$

Finally, an additional constraint ensures that total yearly demand equals the predetermined level x (TWh).

$$\sum_{t,n} q(t,n) = x\,TWh \tag{7.25}$$

The QCP is coded in the GAMS modeling environment. The size of the application here (10.1 GB) makes it necessary to use advanced computers. Computation times with facilities available at DIW Berlin (64-bit Linux, 32 kernels, 3 GHz CPU, 512 GB Ram) range in the order of 11-33 hours, including data compilation and export.

7.4 Data

In general it was taken care to align assumptions to the National Grid Development Plan (TSO 2012) so as to allow for a comparison of results. As the Grid Development Plan does not provide a lot of detailed information on assumptions and used data, some input assumptions of the model used here deviate from the TSO Plan.

7.4.1 Geographic coverage

The model application covers Central Europe with 41 nodes. 18 thereof lie in Germany, in line with the dena-Zones established based on congestion patterns in the seminal dena-II-study (dena 2010). All countries other than Germany and Denmark are represented with one node only.

7.4.2 Temporal coverage

The model is applied to the European electricity system as we expect it to be in 2030. Within the fictive year 2030, an hourly dispatch of the whole year (8760 h) is optimized.

7.4.3 Generation

The model application includes six dispatchable generation technologies plus must-run feed-in of wind, solar and hydro plants. Inflexibilities in the dispatch of fossil-fired and nuclear power plants are reflected by constraints on load gradients and ramping cost. Variable costs are in line with assumptions in the TSO report and produce a merit order curve plotted in Figure 35. Since the model is applied to the year 2030, assumptions are made on the generation capacity available by 2030. The Platts European power plant database (Platts 2011) is used as basis to exogenously determine the retiring dates for all power plants in Europe and thereby attain remaining generation capacities. We expect over 60 GW of installed conventional capacity to retire within Germany by 2030 (compared to 104 GW base level in 2010) which is almost double the 33 GW expected in Maurer et al. (2012). Information on energy plants found in Platts (2011) is combined with geographical information of pre-defined congestion zones to allocate power plants to zones. Capacities deviate between the National Grid Development Plan (TSO 2012) and our assumptions. Scenario B 2032 of the Grid Development Plan is characterized by a high amount of new gas power plant capacities in Southern Germany. The report does not specify how it determines the amount of new capacity and where exactly it is placed. We therefore opt to base or own assumptions on Platts (2011) and optimize the distribution and technology choice of new capacities endogenously. Table 17 provides further details on the base assumptions.

in GW	NEP Scenario B 2032 (TSO 2012)	Own estimations on the basis of Platts (2011)
Lignite	13.9	9.0
Coal	21.2	20.6
Gas	40.1	8.4
Oil	0.5	0.8
Nuclear	0	0
Biomass	9.4	9.4

Table 17: Generation capacities in Germany in the reference scenario.

(Source: Own compilation)

	Wind Index (IWR 2012)	**Solar Index** (SFV 2012)
2005	- 12.8%	+ 1%
2006	- 3.9%	+ 3%
2007	+ 2.7%	+ 3%
2008	+ 1.7%	+ 2%
2009	- 9.2%	+ 2%
2010	- 25.1%	- 4%
2011	+ 2.3	+ 9%
	Deviation from rolling 10-year average	Deviation from 2005-2012 average

Table 18: Wind and solar production 2005-2011 in Germany.

(Source: Own compilation)

The growth of renewable energies in all countries else than Germany is based on projections of productions outlined in EcoFys et al. (2011) which are based on NREAP. Construction of feed-in time series for fluctuating RES is based on meteorological information (Dee et al. 2011; Eurostat 2011) and actual production data of Germany from 2011. Calculations are based on the reference year 2011 as this year represents a relatively good average year in terms of wind production in Germany, see Table 18. Further details on the derivation of power output from solar radiation and wind speed data can be found in Boldt et al. (2012). The time series expose a German peak demand of 84 GW just as in the TSO grid plan. Maximal residual load of reference demand is 76.2 GW on a November day, peak simultaneous feed-in of solar and wind power amounts to 106.7 GW (with 157 GW installed capacity), the minimum lies at 1.4 GW. Peak excess supply of solar and wind feed-in amounts to 33.1 GW. Note that these figures refer to reference demand. As demand is endogenous and price-sensitive in the model, deviations can occur in the resulting actual demand.

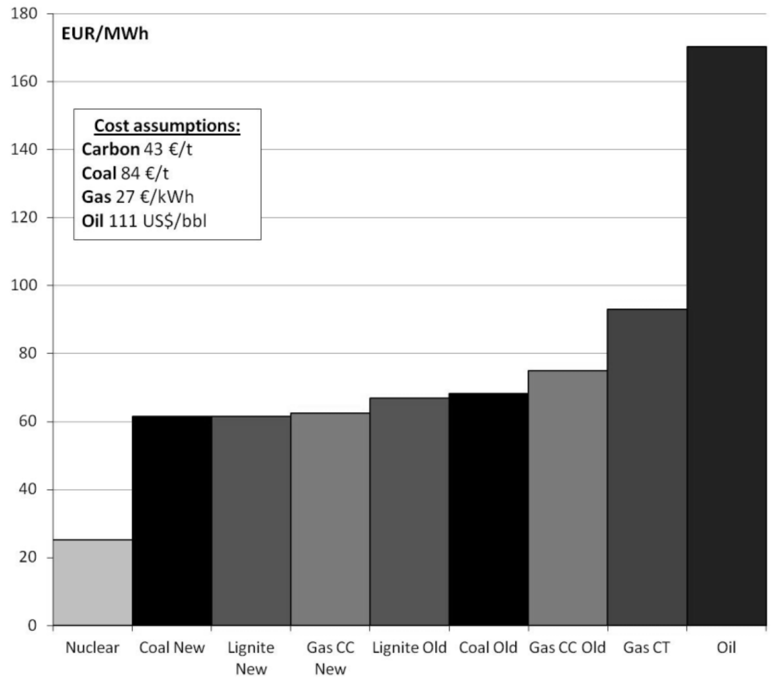

Figure 35: Variable generation cost.

(Source: Own illustration)

7.4.4 Demand

For all scenarios, German net power demand equals 535 TWh per year, including industry demand. This is equal to the 2010 realization of net demand (TSO 2012). While total yearly demand is fixed in the model, its actual repartition over time is endogenous. Demand is determined through a price-sensitive linear demand function with elasticity -0.1. Growth of the reference demand outside Germany is set at 9.3% absolute growth between 2011 and 2030.

7.4.5 Storage & DSM

Three storage technologies are included as measures to flexibilize supply: Adiabatic Compressed Air Storage (aCAES; 4 GW and 16 GWh in Germany), Pump Storage (9 GW and 60 GWh in Germany) and Battery storage (5 GW and 40 GWh in Germany). The aCAES figure is half of the potential identified for Germany in Gillhaus et al. (2006). Three categories of DSM possibilities are included as measures to flexibilize demand. The cost for shifting consumer load is described with a step-wise increasing cost function in order to account for consumer heterogeneity: Low-cost household DSM (3 EUR/MWh), medium-cost commercial DSM (5 €/MWh) and high-cost industrial DSM (10 EUR/MWh). Up to 20% of the reference demand level can be shifted within a range of 2 hours.

7.4.6 Grid

Regarding the grid structure for 2030 (topology and capacities) we refer to the work performed in Boldt et al. (2012) and the recently published plans of the German Transmission System Operators (TSO 2012). Their projections take into account the Ten-Year Network Development Plan of the European Transmission System Operators and further planned projects. The application includes 41 nodes, 263 lines in the AC grid and 50 DC lines.

7.5 Scenarios

8 scenarios are established which allow for a detailed insight into the effect of storage, DC lines and power plant investment on grid congestion. The reference scenario (1) is characterized by the assumptions of the TSO Grid Development Plan scenario B 2032 regarding new transmission line projects and the existence of storage facilities. Alternatively, we propose a storage scenario (2a) in which we add two types of storage facilities in Germany as well as the possibility of DSM, while holding the grid structure unmodified. A No-HVDC-scenario (2b) describes the same situation as in 2a but without HVDC lines. A Few-HVDC-scenario (2c) includes just a subset of the HVDC lines proposed by the TSOs. A power-plant-placing scenario with the proposed HVDC lines (3) runs scenario 1 with endogenous generation capacities. The same holds for the power-plant-placing scenarios with storage and HVDCs (3a), without HVDC (3b) and with few HVDC (3c). Table 19 summarizes the main scenario characteristics.

Scenario	**DSM**	**Storage**	**German HVDC**	**Power plant**
1 – Reference	-	-	28 GW	-
2a – Storage	✓	✓	28 GW	-
2b - No HVDC	✓	✓	-	-
2c - Few HVDC	✓	✓	14.6 GW	-
3 – 1 with investment	-	-	28 GW	✓
3a – 2a with investment	✓	✓	28 GW	✓
3b – 2b with investment	✓	✓	-	✓
3c – 2c with investment	✓	✓	14.6 GW	✓

Table 19: Scenario overview.

(Source: Own production)

7.6 Results

7.6.1 Generation

Figure 36 shows the generation pattern over the whole year in hourly resolution. Lignite and coal power plants are used as base load technologies unless RES feed-in is too strong. Note that at the assumed carbon price of 43 EUR/t, gas power plants are still called after coal-fired plants in the merit order (not taking into account cycling cost). Gas power plants are only called upon at few occasions, in times where RES feed-in is weak. Additionally, gas power plants are used during short intervals in periods of high fluctuations of renewable energies due to their low ramping costs. This pattern pertains to all scenarios and is exemplarily pictured for the reference scenario in Figure 36. Details on the usage of different several generation technologies can also be found in Table 20 where different scenarios are compared. The table demonstrates that all fossil-fired plants are increasingly used as HVDC transmission capacities are eliminated or reduced (3b, 3c). The scenarios with endogenous investment shift the power mix towards increased usage of new gas-fired power plants, to the detriment of all other fossil-fired plants. Oil power plants are not used at any instance anymore for they are too expensive with the assumed 43 EUR/t CO_2 prices in 2030. The system-wide share of RES production lingers around the 52% mark with slight deviations. Storage and DSM improve the share of RES in Germany slightly from 76.3% to 76.5% in the presence of HVDC lines. Scenarios 2b and 2c with no to few HVDC lines produce a lower system-wide RES share than other scenarios. This suggests that HVDC is indeed used to promote the RES share in the system. We find a systematic negative effect of endogenous power plant investment on the RES share which is a pretty obvious result.

The net power consumption is in line with the TSO assumptions of 535 TWh in Germany (TSO 2012). A constraint in the model ensures this amount of yearly demand. Power production levels in Germany are lower than the demand level in most scenarios. As power generation is short of demand, Germany is a net importer of electricity by 2030 in most scenarios, contrasting the situation of 2012. We owe this effect to the increased price differences between countries with fossil-based production versus those with constant hydro production (Scandinavia) and nuclear energy (i.e. France). As German prices increase more than proportionately to some neighbors' power prices, there is increased import. The import rate increases with the use of storage and DSM in scenario 3a. HVDC lines seem to have an aggravating effect on electricity import of Germany. The more HVDC lines in Germany, the higher is the import rate of Germany. As HVDC disappear (scenario 2b), cheap northern German energy cannot be transported to southern demand zones and thus needs to be exported to neighbors.

We observe no systematic effect of HVDC lines, power plant investment and storage on demand levels by nature of the model constraints. The effect of storage and HVDC lines on the average German price level is somewhat counter-intuitive. The presence of HVDC lines puts upward pressure on German average prices. This could be due to the fact, that average prices are not weighed by importance of nodes.

	NO INVESTMENT				WITH INVESTMENT				NEP 2012
Scenario	1	2a	2b	2c	3	3a	3b	3c	B 2032
	Reference	Storage	No HVDC	Few HVDC	Reference	Storage	No HVDC	Few HVDC	B 2032
Investment GW Europe	-	NEP Capacity	NEP Capacity	NEP Capacity	23,327	23,255	32,154	23,303	-
Investment GW Germany	-	NEP Capacity	NEP Capacity	NEP Capacity	0	0	5,348	0	-
RES share system-wide	52.30%	52.38%	51.72%	52.20%	52.05 %	52.15%	51.45%	51.96%	
RES Share of production in Germany	76.31%	76.46%	76.53%	76.36%	76.33%	76.50%	76.53%	76.39%	
Yearly demand in D in TWh	535	535	535	535	535	535	535	535	562
Yearly production in D in TWh	482	488	549.2	495	480.5	480.3	510.2	488	550
Export rate	-9,96%	-8.84%	2.65%	-7.48%	-10.19%	-10.23%	-4.64%	-8.82%	-2.06%
Use rate all AC lines	24.7%	24.7%	24.4%	23.9%	24.6%	24.6%	24.8%	23.9%	-
Use rate all DC lines	90.3%	90.2%	95.8%	79.4%	90.2%	90.4%	95.9%	79.6%	-
Use rate of proposed HVDC line projects	78.97%	78.88%	-	89.51%	79.38%	79.74%	-	90.48%	
German average price EUR/MWh	57.26	56.75	54.35	56.76	57.08	57.29	54.06	57.39	-
Welfare in billion EUR	9.73068E+11	9.733E+11	9.69411E+11	9.73873E+11	9.74321+11	9.74500E+11	9.70739+11	9.74057+E11	-
Full Load Hours Lignite	4933	4437	4931	4422	4598	4625	4562	4617	-
Full Load Hours Coal (Old)	1799	1685	2126	1760	1560	1575	1747	1638	-
Full Load Hours Coal (New)	-	-	-	-	-	-	-	-	-
Full Load Hours Gas (Old)	2089	1580	1757	1604	805	764	768	795	-
Full Load Hours Gas (New)	-	-	-		7377	7388	7136	7415	-
Full Load Hours Oil	176	175	173	175	1	1	0	1	-
Full Load Hours Nuclear (abroad)	7863	7869	7327	7839	7870	7876	7333	7847	-

Table 20: Key results of scenarios.

(Source: Own compilation)

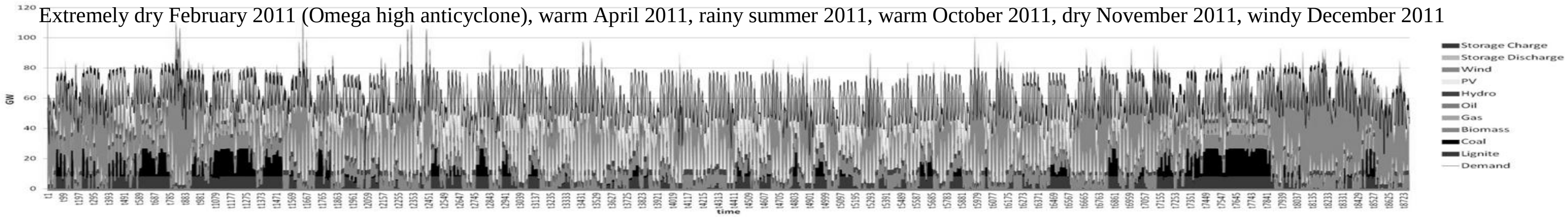

Figure 36: Generation dispatch pattern in the reference scenario.

(Source: Own compilation)

7.6.2 Investment

Results show that optimal capacity expansion levels for most technologies are much lower than previous "reference" studies propose for Germany (EWI et al. (2010); dena (2008); EC (2011)). This holds across all technologies. A possible explanation is that investment cost and carbon prices are set too low in the reference studies. Furthermore, many studies disregard dispatch inflexibilities of coal and lignite technologies and omit the possibilities of flexible demand and storage. However, we must admit that the model used here may undervalue the necessity of power plants because not accounting for uncertainty in RES feed-in and demand.

Table 20 shows the level of overall EU capacity expansion by 2030 for all scenarios. Capacity expansion in Germany is zero except in the absence of national HVDC lines in scenario 3b. Figure 37 shows that capacities are foremost planted in the southern to central zones, and Hamburg.

The model application suggests that investment into roughly 23-32 GW of gas-fired power plants be undertaken in south and Central Eastern Europe (Italy and Slovenia). We explain the (comparatively) low level of overall investment by the fact that other studies omit or underestimate the value of storage and DSM. According to Maurer et al. (2012), DSM and storage can only contribute little to reducing capacity needs. They argue that DSM and storage are designed to shift loads for few hours whereas supply shortages can occur with longer durations. The results here show that hydro pump storage and other facilities are also used for seasonal storage, thus showing great value in the short term as well as in the long term.

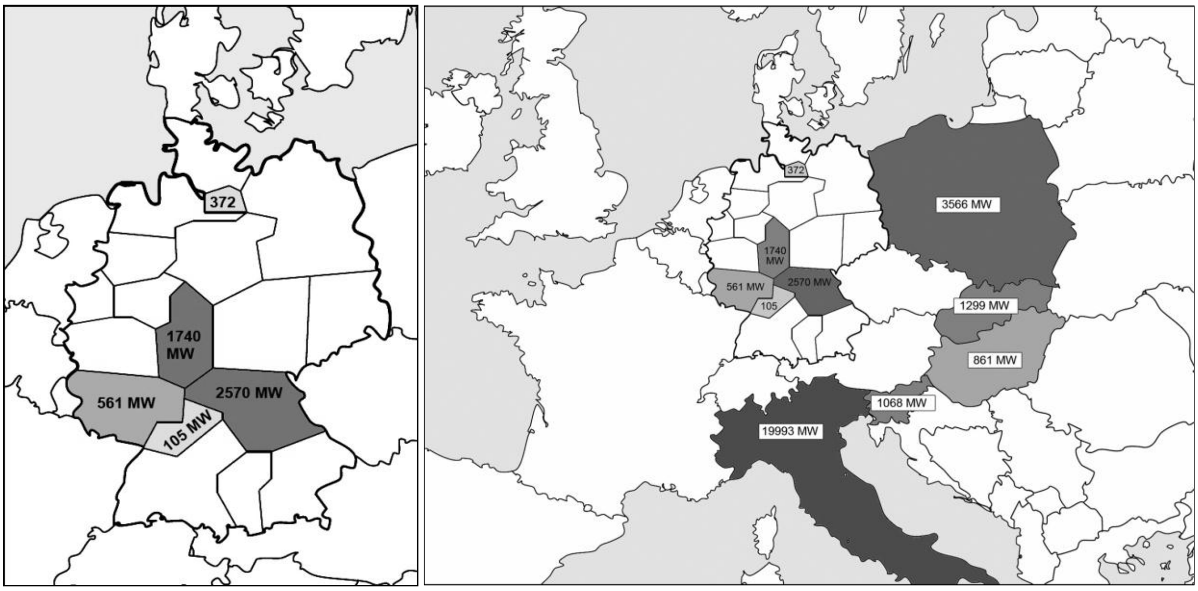

Figure 37: New generation capacity by 2030 in the absence of national HVDC lines.

(Source: Own illustration)

Regarding the technology choice, gas-fired power remains dominant in all scenarios, although it lies behind coal in the merit order. Concentration on gas-fired plants is also due to increased need for flexible resources with low ramping cost. 5,348 MW of gas-fired power plants are placed in Central and Southern German zones in scenario 3b, in the absence of HVDC lines (Figure 37). In all other scenarios, no power plant investment takes place in Germany. We conclude that even under strong decommissioning - as assumed in this study here – the model predicts hardly any need for new power plants in Germany with storage, demand-side-management and HVDC line extensions providing for sufficient alternatives. As indicated by the volatile generation profiles in Figure 36, new power plants – if built - will require good cycling capabilities. Such importance of cycling flexibility in the investment decision has also been pointed out in a related analysis carried-out by Fleten and Nasakkala (2010). The role of cycling cannot be accounted for in full detail in this study, since a more detailed analysis would require a stochastic model.

7.6.3 Congestion AC Grid

Regarding the congestion patterns inside Germany, Figure 38 provides details for the standard grid (without German HVDC lines). Connections whose capacity limit is exhausted in less than 20% of the time are shown in yellow color. Connections with more than 40% of congested time and more than 60% are orange and red, respectively. Connections highlighted in dark red are overloaded more than 80% of the hours observed.

The comparison between the reference scenario (1) and the storage scenario with HVDC (2a) shows little changes. However scenario 3c demonstrates that the there is less congestion on a few south-northern routes in absence of HVDC lines. This is true especially for the links 41-42, 24-25 and 83-25 in central southern Germany. The relatively strong bottlenecks in scenario 3b can be relieved by the placement of 14.6 GW of HVDC lines in scenario 3c. Overall, we conclude that in scenario 3c, a reduced amount of HVDC capacity is a sufficient measure to avoid severe shortages in the domestic AC grid. Scenario 3c shows that 14.6 GW of HVDC lines are able to bringing congestion in the German power grid to a level relatively close to the reference scenario with 28 GW HVDC capacity. The placement of additional power plants (ca. 5.3 GW in Germany) in scenario 3b is not sufficient to relieve bottlenecks to the level of the reference scenario.

1 – Reference   3b – Storage but no HVDC   3c – 14.6 GW HVDC

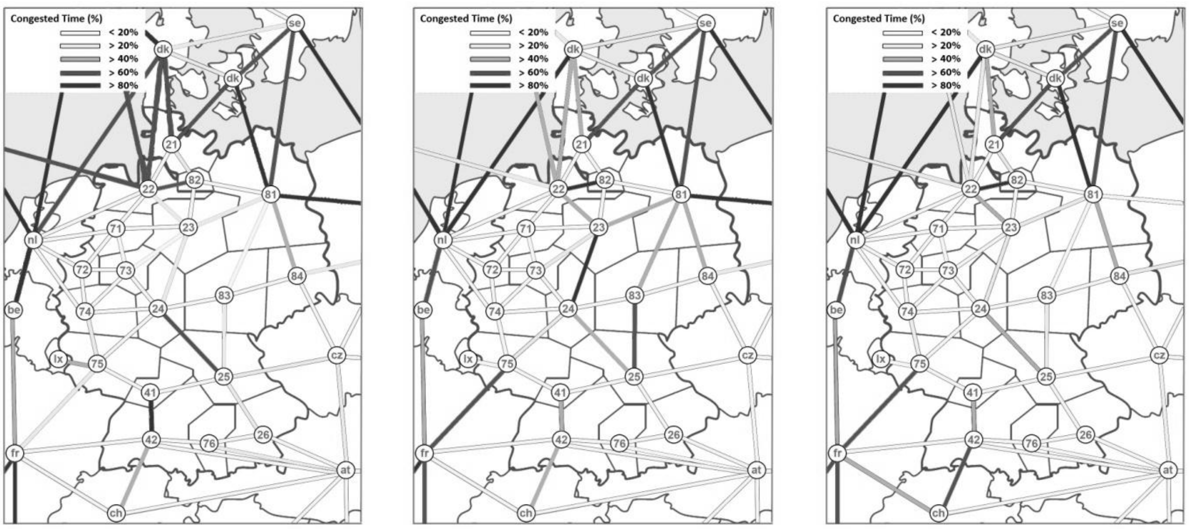

Figure 38: Congestion patterns in the standard grid.

(Source: Own illustration)

7.6.4 Congestion on HVDC lines proposed in the NEP 2012

While the HVDC lines proposed by TSOs contribute to less congestion in the AC grid, the HVDC lines themselves are mostly used to a high extent, as plotted in Figure 39. The figure only pictures the situation in the reference scenario. Its structure remains unchanged in other scenarios, though. The average use rate is depicted on the right side of the graph and it is consistently high for most lines, except for some lines on the north-south corridors B, C and D. The left side shows the hours of congestion as percentage. We see that some HVDC lines of the C Corridor between zones 21, 22 and the southern zones 42 and 25 are overloaded over 40% of the time. Most lines on the C Corridor are often overloaded. Given the large dimensions of the range of 12 GW of transmission capacity of corridor C, this is an interesting result. The large capacity of this connection appears to be fully justifiable. The right part of the same chart shows that some lines in the Northwest part of the Republic have high average usage rates, although congestion is not as frequent as in the corridor C. This holds particularly for the HVDC transmission line 1 from Emden to Osterath (22-72), which has a high average utilization rate over 85% - yet it is used to full capacity less than 40% of the time. The situation is quite different for HVDC lines in the southwest and northeast. The average utilization of the HVDC links 10 from Gustrow to Meitingen (81-76) and 9 from Lauchstaedt to Meitingen (83-76) are relatively low. The same is true for the HVDC transmission line 2 from the Rhenanian lignite mining area in Osterath to Philipsburg (72-41) and Elsfleth-Philipsburg (22-41). One might raise the question of the lines' usefulness. Due to the relatively low utilization of some HVDC lines, we investigate scenarios which deviate from the configuration of an HVDC network as proposed by the TSOs. Due to the non-existence of HVDC transmission capacity in scenarios 2b and 3b, congestion is transferred from the DC to the AC grid where new bottlenecks occur. In scenarios 2c and 3c, we propose the construction of only 14.6 GW of HVDC lines instead of 28 GW. It can be seen that the remaining HVDC lines are in good utilization of around 90% with a positive impact on the overall network. A value of 90% comes close to the use rates of traditional HVDC interconnectors between countries.

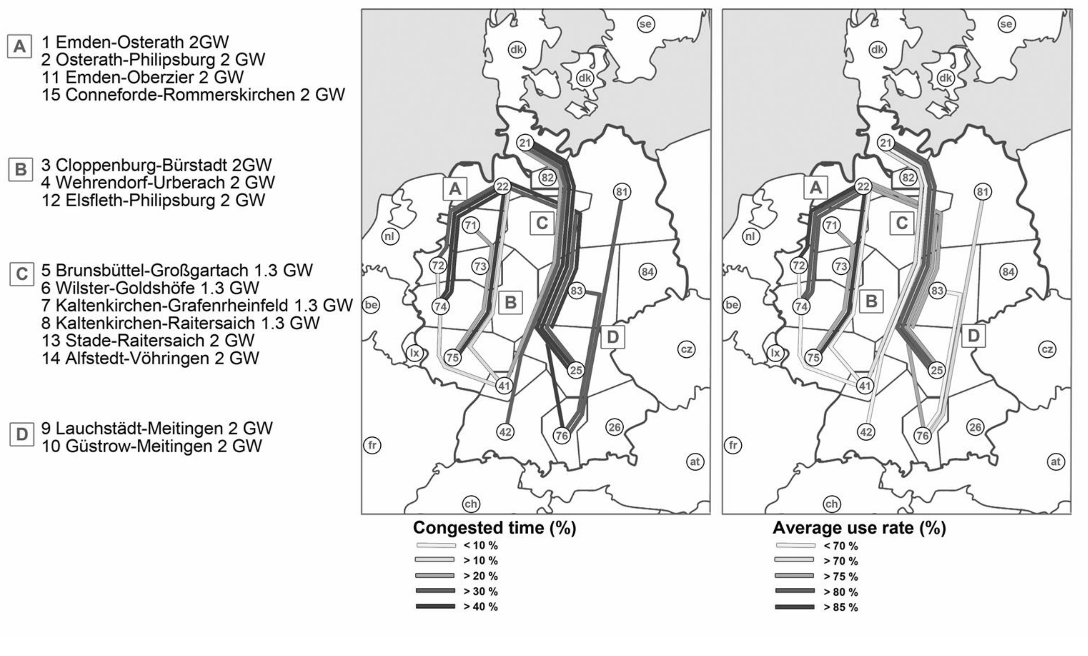

Figure 39: Congestion on HVDC lines proposed in the NEP 2012 (reference scenario).

(Source: Own illustration)

A further detailed analysis of congestion patterns on the different corridors is illustrated in Figure 40. All in all, corridors B & C are seldomly used to capacity (less than 10% of the time). Corridor A and B are used to full capacity at less than 20% of the time. The use rate of corridor D is lowest of all corridors, followed by corridor B. Note that use rates and congested times within corridor C vary greatly, as indicated in Figure 39. In scenario 3a, storage seems to be complementary to better usage of HVDC lines in times where lines are not congested. In scenario 3c, the two corridors are almost always used to full capacity. We may conclude from the analysis above, that the necessity of the HVDC lines proposed in the TSO plan varies greatly case by case. While all corridors do show some positive impact on relieving congestion in the AC grid, there seem to be some individual links which have little to no positive impact. A prioritization of HVDC projects may thus be a good step to reduce costs of grid expansion while equally ensuring the advantages that HVDC lines provide for the grid system.

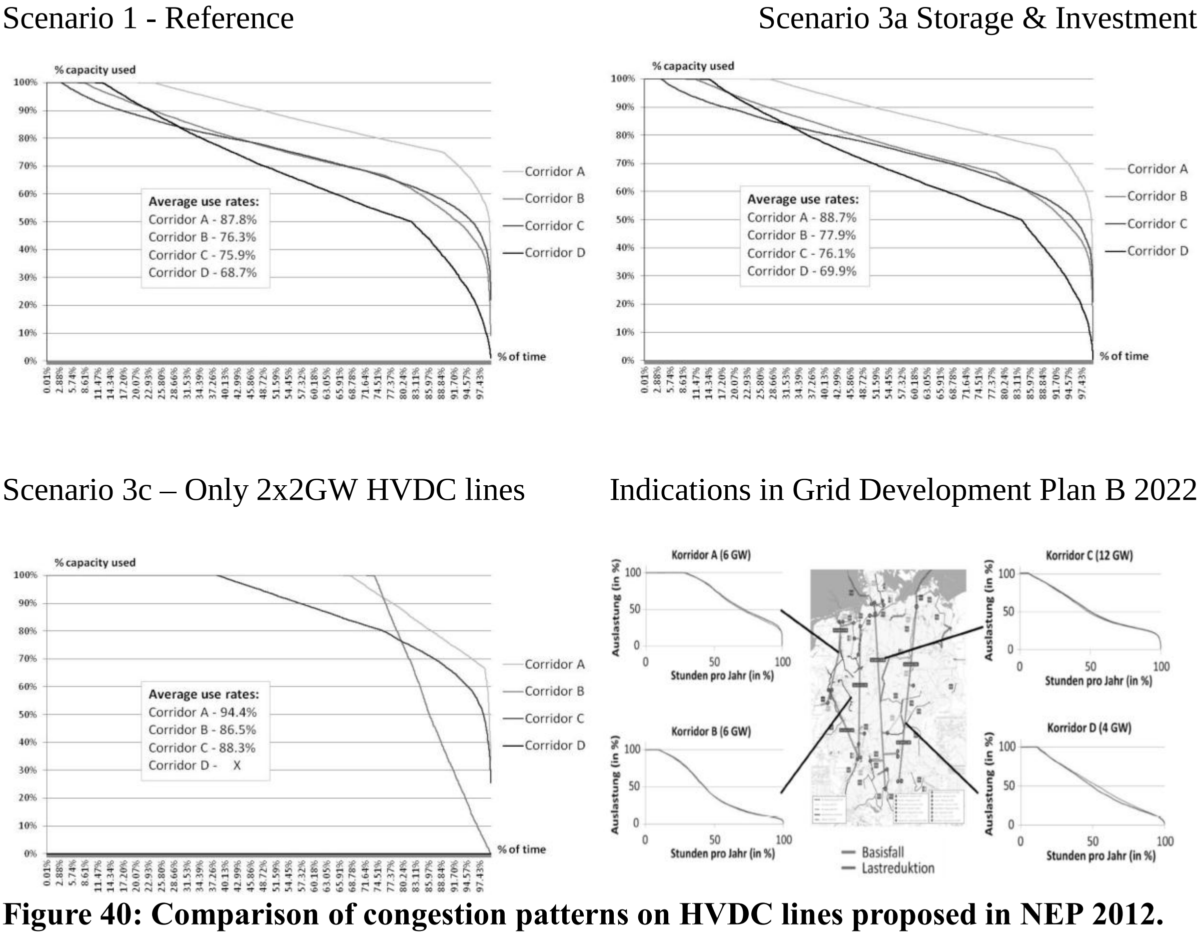

Figure 40: Comparison of congestion patterns on HVDC lines proposed in NEP 2012.

(Source: Own illustration and TSO (2012, p.169))

7.6.5 Price differences

A basic assumption of the model application is that German producers and consumers face nodal prices. While such market design is not in force today, we assume that it is going to be implemented by 2030. As shown in Figure 41, nodal prices within Germany align around 54-

61 EUR/MWh in the reference scenario. Regional differentiation is low. This result can easily explained by the balancing effect of massive HVDC capacity. As soon as this is left out, prices between regions drift apart quite heavily, as shown in the middle section of Figure 41. A huge price differential between exporting northern zones and importing southern zones emerges. The right side of the graphs demonstrates that DSM, storage management and power plant placing manage to bring the price structure closer to its reference case even in the presence of only 14.6 GW of HVDC lines. However, effects are only local, and Germany remains affected by price developments in neighboring states.

1 Reference | 2b Storage but no HVDC | 3c Investment & 14.6 GW HVDC

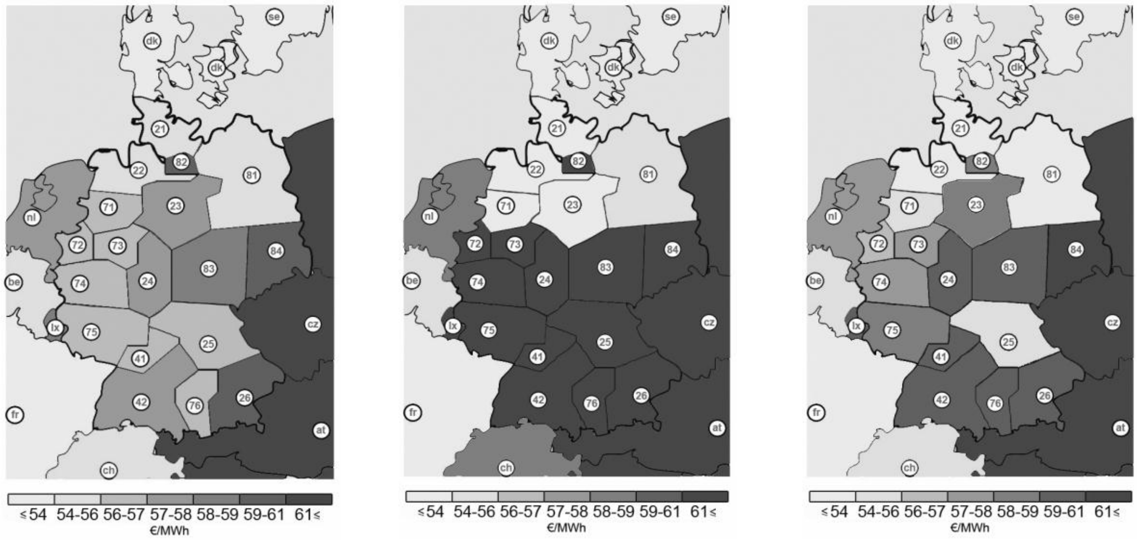

Figure 41: Prices in different scenarios.

(Source: Own illustration)

7.7 Conclusions

This chapter presents a model for the analysis of power plant placing and grid congestion. An application is done for Central Europe in 2030 and congestion patterns are compared to the Grid Development Plan of the German TSOs (TSO 2012). We find that HVDC lines as proposed in the German Grid Development plan are useful in relieving overall congestion. However, some lines have less impact on overall congestion than others and could be marked as second priority. A prioritization of HVDC projects would be an appropriate measure to ensure that the positive effects of HVDC lines prevail.

The analysis shows that a mix of few HVDC lines, storage, DSM and the placement of power plants can contribute to alleviating the need in expanding power transmission capacity. Overall investment levels into generation capacity are way lower in our results compared to related studies (e.g. dena (2008); EC (2011); EWI et al. (2010); Maurer et al. (2012), TSO (2012)). We conclude that many comparable models over-estimate the necessity of power plants by omitting the flexibilities offered by storage, DSM and increased grid capacities. We suggest it would be beneficial to coordinate the planning of power plant investment along with grid system planning.

The need for transmission capacity expansion and generation capacity investments are the focus of the application presented here. It should be subject of another line of research (Sauma & Oren 2009; Milstein & Tishler 2012) whether sufficient investment incentives are present in today's liberalized energy-only markets. Similarly, subjects such as security of supply and risk aversion of planners deserve more attention (van der Weijde & Hobbs 2012) and should possibly be modeled with tools that include uncertainty in demand and RES feed-in.

7.8 Appendix

Sets	s	Set of all plant types
	n	Set of all nodes
	l	Set of all line
	dcl	Set of all DC lines
	t	Set of all times/hours
	st	Set of all storage types
Parameters	ε	Demand elasticity at reference point
	λ	Factor defining load levels
	$AC_{p_{max}}(l)$	Maximum capacity of line l
	$DC_{p_{max}}(l)$	Maximum capacity of line dcl
	$DSM_{MAX_h}(t,n)$	Maximum capacity of demand-side management at high cost
	$DSM_{MAX_l}(t,n)$	Maximum capacity of demand-side management at low cost
	$DSM_{MAX_m}(t,n)$	Maximum capacity of demand-side management at medium cost
	$S_{IN_{max}}(st,n,t)$	Maximum storage inflow
	$S_{OUT_{max}}(st,n,t)$	Maximum storage outflow
	$S_{cap_{max}}(st,n)$	Storage capacity limit
	$hydro_{max}(t,n)$	Maximum of energy generation by hydro powered plants
	$Cost_{DSM}(s)$	Cost for DSM
	$Cost_{INVEST}(s,n)$	Investment Costs for plant type s in node n
	$Cost_{ramp}(s)$	Marginal ramping costs
	$DC_{incidence}(dcl,n)$	Incidence matrix
	$G_{max}(n,s)$	Maximum of generation capacity at node n of plant s
	Lim_{ramp}	Limit of ramped up generation capacity
	$Perc_{ramp}$	Load Gradient as percentage of nominal capacity
	$S_{eff}(st)$	Conversion efficiency storage
	$p_{ref}(t)$	Reference price of demand function at t
	$pv_{max}(t,n)$	Maximum of energy generation by photovoltaic power

	$q_{ref}(t)$	Reference demand at t
	$wind_{max}(t,n)$	Maximum of energy generation by wind power
	$c(s)$	Cost for plant type s
	$m(t,n)$	Slope of demand function
	$ptdf(l,n)$	Power transfer distribution factor concerning node n and line l
	$rev(s)$	Factor defining the availability of plant type s
	x	Predetermined level of yearly demand
Variables	$AC_{lineflow}(l,t)$	Line flow on l
	$AC_{netinput}(t,n)$	Net input on node n
	$Cost_{var}(t)$	Total generation cost
	$DC_{lineflow}(dcl,t)$	Line flow on dcl
	$DC_{netinput}(t,n)$	Net input at node n
	$q_{area}(t)$	Area under demand function
	W	Welfare
Positive Variables	$DSM_{OUT_h}(t,n)$	DSM shifting load at high cost
	$DSM_{OUT_l}(t,n)$	DSM shifting load at low cost
	$DSM_{OUT_m}(t,n)$	DSM shifting load at medium cost
	$DSM_{IN_h}(t,n)$	DSM adding load at high cost
	$DSM_{IN_l}(t,n)$	DSM adding load at low cost
	$DSM_{IN_m}(t,n)$	DSM adding load at medium cost
	$I(s,n)$	Investment into generation capacity
	$S_{IN}(st,n,t)$	Storage inflow
	$S_{LEVEL}(st,n,t)$	Storage level
	$S_{OUT}(st,n,t)$	Storage outflow
	$g_{up}(t,s,n)$	Generation change from one period to the next
	$q(t,n)$	Demand at node n
	$G(n,s,t)$	Generation of plant type s of firm f at node n

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Appendix – Source Codes

Major parts of the codes of the developed models are collected here and further information and data can be retrieved upon request at the author of this thesis. In making the use of data and model code transparent, the Thesis abides by the “Ethical code for appropriate scientific behavior for economists” set out by the Verein fuer Socialpolitik (VfS 2012), requiring, amongst other things, that research be transparent and tractable, and that data, source code, and results be made publicly available.

GAMS Code of the model in Chapter 2

```
*==================================================================================
* Andreas Schröder 23. October 2010
* Model on sizing of storage and DSM applicances.
* Version with Benders Decomposition per Scenario and Feasibility cut. Winter season.
* Stochastic wind feed-in and demand. DSM_max deterministic. 5-Node-Grid included.
* System Cost Minimization
* Model run requires access to the file: „input-smart-grid-umgebaut-fuer-stochastik-jahreswerte-9.xls“
*==================================================================================


* set key parameters
$set iter_max 40
$set dsm_cost  4.02
$set storage_cost  0.04
$set dsm_limit_per_node  360

*##########################################################################################
*                              DATA
*##########################################################################################
*------------------------------------------------------------*
* sets  = Indices
*------------------------------------------------------------*

sets
t               time                    / t1 * t24 /
sc              scenario                / 1*30 /
s               type of plant           / chp,pv,hydro,nuclear,lignite,hardcoal,gas,biomass /
l               Line                    / l1*l4 /
n               Node                    / 1*5 /
iter            iteration               /iter1*iter%iter_max%/
ocut(iter)         optimality cut
fcut(iter)         feasibility cut
Alias (t,tt), (s,ss), (l,ll), (n,nn);

ocut(iter) = no; fcut(iter) = 0;


scalar
        alpha_low       lower bound on recourse value   /-50/
        epsilon         stopping criterium              /1e-1/
        converged       one if converged                /0/
        feasible        zero if subproblem infeasible   /0/
;

parameter
*       Needed for benders
        lambda_dsm_inv_iter(iter,n)     dual value of fixed first stage variables
        lambda_scap_max_iter(iter,n)    dual value of fixed first stage variables
        gamma_dsm_inv_iter(iter,n)      dual fixing constraint feasibility sub
        gamma_scap_max_iter(iter,n)     dual fixing constraint feasibility sub
        beta_iter(iter)                 feasibility problem objective
        alpha_iter(iter)                subproblem objective by iteration
        dsm_inv_iter(iter,n)            first stage decision(DSM) by iteration
        scap_max_iter(iter,n)           first stage decision(storage) by iteration
        dsm_inv_fix(n)                  first stage decision scap_max passed to subproblem
        scap_max_fix(n)                 first stage decision dsm_inv passed to subproblem
        lambda_dsm_inv_scen(sc,n)  dual value dsm_inv by scenario
        lambda_scap_max_scen(sc,n) dual value scap_max by scenario
        alpha_scen(sc)                  subproblem objective by scenario

*       Reports
        iterlog                 iteration report of bounds
```

```
    report_iter1          iteration report first-stage variables
    report_iter2_DSM      iteration report second-stage variables DSM
    report_iter2_SIN      iteration report second-stage variables SIN
    report_iter2_SOUT     iteration report second-stage variables SOUT
    report                report parameter
    report_scen           report by scenario
    prob(sc)              probability of scenario

;
prob(sc) = 1/card(sc);

lambda_dsm_inv_iter(iter,n) = 0;
lambda_scap_max_iter(iter,n) = 0;
alpha_iter(iter) = 0;
scap_max_fix(n) = 0;
dsm_inv_fix(n) = 0;
dsm_inv_iter(iter,n) = 0;
scap_max_iter(iter,n) = 0;
lambda_dsm_inv_scen(sc,n) = 0;
lambda_scap_max_scen(sc,n) = 0;
alpha_scen(sc) = 0;
beta_iter(iter)=0;
gamma_dsm_inv_iter(iter,n)=0;
gamma_scap_max_iter(iter,n)=0;

*------------------------------------------------------------*
* Generation Parameters
*------------------------------------------------------------*

Parameter g_max(t,s,n) maximal plant capacities;

Parameter g_max_grid_supply_point(t,s) maximal plant capacities at Grid Supply Point in kW;
$LIBINCLUDE XLIMPORT G_max_grid_supply_point input-smart-grid-umgebaut-fuer-stochastik-jahreswerte-9.xls production1!ad5:al29

Parameter g_max_zero(t,s) maximal plant capacities at Grid Supply Point in kW;
$LIBINCLUDE XLIMPORT G_max_zero input-smart-grid-umgebaut-fuer-stochastik-jahreswerte-9.xls production1!ff5:fo29

Parameter g_max_distributed_generation(t,s) maximal plant capacities at Grid Supply Point in kW;
$LIBINCLUDE XLIMPORT G_max_distributed_generation input-smart-grid-umgebaut-fuer-stochastik-jahreswerte-9.xls production1!et5:fc29

g_max(t,s,'1') = g_max_grid_supply_point(t,s);
g_max(t,s,'2') = g_max_zero(t,s);
g_max(t,s,'3') = g_max_distributed_generation(t,s);
g_max(t,s,'4') = g_max_zero(t,s);
g_max(t,s,'5') = g_max_zero(t,s);

Parameter g_wind_max(t,sc,n) maximal wind power capacities at Grid Supply Point in kW;

Parameter g_wind_max_grid_supply_point(t,sc) maximal plant capacities at Grid Supply Point in kW;
$LIBINCLUDE XLIMPORT g_wind_max_grid_supply_point input-smart-grid-umgebaut-fuer-stochastik-jahreswerte-9.xls production1!at5:bx29

Parameter g_wind_max_zero(t,sc) maximal plant capacities at Grid Supply Point in kW;
$LIBINCLUDE XLIMPORT g_wind_max_zero input-smart-grid-umgebaut-fuer-stochastik-jahreswerte-9.xls production1!dm5:eq29

g_wind_max(t,sc,'1') = g_wind_max_grid_supply_point(t,sc);
g_wind_max(t,sc,'2') = g_wind_max_zero(t,sc);
g_wind_max(t,sc,'3') = g_wind_max_zero(t,sc);
g_wind_max(t,sc,'4') = g_wind_max_zero(t,sc);
g_wind_max(t,sc,'5') = g_wind_max_zero(t,sc);

Parameter g_wind_max_scen(t,n)  maximal wind power capacities at Grid Supply Point in kW;
Parameter gen_per_node(t,s) generation per node for reporting;

display G_max;

parameter G_c(s)     marginal generation costs in EUR per KWh
/
chp 0.0003
pv 0.0002
hydro 0.0004
nuclear 0.01
lignite 0.04
hardcoal 0.06
gas 0.07
biomass 0.0005
/
;
Scalar g_wind_c marginal generation cost in EUR per kWh for wind /0.002/;

*------------------------------------------------------------*
* Demand Parameters
*------------------------------------------------------------*

Parameter q_ref(t,sc,n)      reference demand in kW;
Parameter dem_per_node(t,sc) for reporting;
```

```
Table q_ref_demand_node(t,sc)       reference demand in kW in summer
       1       2       3       4       5       6       7       8       9       10      11      12      13      14      15      16      17      18      19      20
21      22      23      24      25      26      27      28      29      30
t1      112     120     129     113     129     119     118     115     124     117     118     132     129     120     114     128     117     118
119     125     123     121     127     124     116     112     123     117     123     120
t2      95      97      92      85      91      81      94      101     94      93      93      95      96      93      89      86      98      93      90
89      91      88      96      102     97      93      95      101     95      99
t3      77      78      76      80      82      80      76      80      83      80      74      84      81      79      77      82      82      81      78
80      79      82      86      81      71      77      82      81      74      77
t4      73      71      76      77      76      78      72      72      79      77      72      72      74      69      70      73      66      73      82
71      71      74      76      76      65      71      77      68      71      78
t5      74      71      69      74      75      70      74      72      66      75      77      68      69      69      64      71      79      71      72
69      68      69      72      73      74      70      68      70      69      70
t6      65      72      76      77      70      68      70      77      77      77      67      82      72      74      68      75      71      73      72
73      78      73      71      76      76      75      68      73      74      75
t7      85      81      83      78      74      81      78      77      71      76      76      77      78      80      82      80      74      81      76
81      74      78      73      78      76      80      92      78      85      74
t8      96      101     98      102     101     96      97      99      95      98      98      95      101     96      97      95      98      94      97
95      94      97      98      99      95      95      100     97      96      93
t9      107     129     114     112     117     119     122     127     112     105     122     115     133     119     119     120     126     110
116     121     115     120     132     120     111     121     123     119     117     122
t10     138     125     135     120     135     137     124     117     126     119     118     137     126     107     134     141     147     136
141     134     127     135     125     147     135     143     121     127     124     125
t11     123     128     137     131     150     117     139     127     138     129     140     147     141     133     150     142     144     135
107     128     152     111     127     139     128     127     121     134     123     127
t12     133     140     133     134     131     144     135     122     131     139     134     123     144     132     138     116     143     130
134     136     144     136     126     141     150     137     130     134     137     120
t13     142     129     114     130     131     135     136     133     132     144     128     153     146     137     134     148     157     129
143     137     132     147     146     137     137     149     141     137     138     153
t14     149     155     146     146     156     147     148     142     139     140     152     136     150     146     147     153     153     142
139     151     144     160     142     153     136     131     150     152     133     138
t15     127     126     142     124     138     142     132     151     137     134     136     149     140     140     144     129     135     140
136     143     148     145     148     121     142     150     147     128     143     140
t16     135     127     140     124     127     124     140     130     151     152     146     157     146     135     137     149     138     132
140     143     111     138     127     139     131     133     142     143     135     138
t17     139     145     137     148     133     122     145     136     140     147     147     131     135     132     138     141     140     143
142     128     142     145     125     134     134     130     138     150     139     149
t18     140     141     148     136     139     152     153     134     135     146     136     145     131     134     136     140     136     131
124     148     143     133     141     143     156     141     137     134     135     140
t19     155     149     150     149     143     145     142     157     139     138     149     133     143     144     139     144     141     149
144     139     156     145     147     158     146     155     139     151     154     154
t20     141     158     162     155     143     156     165     163     151     150     148     144     146     142     145     155     159     156
153     173     145     138     142     152     150     167     152     158     142     170
t21     154     149     159     139     163     156     160     155     152     156     156     156     153     157     149     160     165     157
149     167     147     165     154     170     158     165     162     162     152     153
t22     157     156     150     162     152     157     161     160     151     163     147     150     149     149     146     157     156     157
160     160     163     161     151     151     150     152     165     163     158     154
t23     170     162     142     153     146     151     158     150     162     163     163     157     141     170     145     156     154     163
157     161     159     153     156     162     158     151     169     161     150     153
t24     156     153     147     150     135     140     145     147     148     150     149     160     146     150     164     156     146     150
160     151     144     148     149     155     142     153     145     149     149     152
;

Parameter q_ref_zero(t,sc)       reference demand in kW;
$LIBINCLUDE XLIMPORT q_ref_zero input-smart-grid-umgebaut-fuer-stochastik-jahreswerte-9.xls demand1!i5:am29

q_ref(t,sc,'1') = q_ref_zero(t,sc);
q_ref(t,sc,'2') = q_ref_demand_node(t,sc);
q_ref(t,sc,'3') = q_ref_demand_node(t,sc);
q_ref(t,sc,'4') = q_ref_demand_node(t,sc);
q_ref(t,sc,'5') = q_ref_demand_node(t,sc);

Parameter q_ref_scen(t,n)       reference demand in kW ;

display q_ref;


*------------------------------------------------------------------*
* Demand-side management parameters
*------------------------------------------------------------------*

Parameter DSM_max_pos(t,n) Maximum capacity for demand-side management in kW;
$LIBINCLUDE XLIMPORT DSM_max_pos input-smart-grid-umgebaut-fuer-stochastik-jahreswerte-9.xls dsm1!b5:g29

Parameter DSM_max_neg(t,n)  Maximum capacity for demand-side management in kW;
$LIBINCLUDE XLIMPORT DSM_max_neg input-smart-grid-umgebaut-fuer-stochastik-jahreswerte-9.xls dsm1!n5:s29

Scalar dsm_inv_cost investment cost in EUR per household / %dsm_cost% / ;


*------------------------------------------------------------------*
* storage parameters
*------------------------------------------------------------------*

Scalars
Sin_max     input power limit of storage device in kW            / 2600 /
```

```
Sout_max    output power limit of storage device in kW            / 2600 /
S_c         cost of energy from storage device in EUR per kW       / 0.00004 /
S_eff       conversion efficiency of storage device in per cent    / 0.75 /
scap_inv_cost investment cost of storage in EUR per kWh capacity  / %storage_cost% /
;

*------------------------------------------------------------------*
* Line parameters
*------------------------------------------------------------------*

parameter lf_max(l)       Max Capacity of Line in KW in 10kV grid
/
l1      1850
l2      1850
l3      1850
l4      1850
/
;

* Source: DG Grid (2006) for grid level 11 kV and higher.
* Size (mm)   Capacity(Amp)  R (Ohm/km)    X (Ohm/km)        Installation and investment cost (GBP/km/year)
* 70          185            0.443         0.0705            3,062
* 300         420            0.1           0.0675            4,029

parameter Transformer(n)    Maximum power capacity of transformer in kW
/
1      0
2      250
3      250
4      250
5      250
/
;

parameter X(l)            Reactance of Line l
/
l1      0.4
l2      0.4
l3      0.5
l4      0.5
/
;

table Incidence(l,n)      Connects Lines with Nodes (Start(1) -> End(-1))
        1       2       3       4       5
l1      1      -1       0       0       0
l2      0       1      -1       0       0
l3      0       0       1      -1       0
l4      0       0       0       1      -1
;

Parameter H(l,n)          Flow Sensitivity Matrix;
H(l,n) = 1/X(l) * Incidence(l,n);

Parameter B(n,nn)         Network Susceptance Matrix;
B(n,nn) = SUM(l, Incidence(l,n) * H(l,nn) );

Parameter Slack(n)        Slack Paramter (one node delta has to be zero);
slack('1') = 1;


*------------------------------------------------------------------*
* auxilliary quantities - assigned after solving the model
*------------------------------------------------------------------*

parameter q_tot(t,sc,n)    energy demand incl. DSM and storage ;
Parameter lf(t,l)          Line Flow ;
Parameter scap_max_total total storage investment;
Parameter dsm_inv_total total DSM investment;


*#######################################################################################
*                               MODEL FORMULATIONS
*#######################################################################################


*--------------------------------------- MASTER PROBLEM --------------------------------
variables
COST_M              total cost Master Problem
ALPHA               recourse value
;

positive variables
Scap_max(n)           investment into storage capacity in kWh
DSM_inv(n)            investment into DSM capacity absolute number of meters
;
```

```
Equation
        obj_m         master  objective function
        res_ocut      Benders optimality cuts
        res_fcut      Infeasibility cuts
        res_alpha_low lower bound on recourse value
        dsm_inv_fixed
;

obj_M..
        COST_M         =E=     sum(n, scap_max(n) * scap_inv_cost + dsm_inv_cost * dsm_inv(n)) + ALPHA
;

res_ocut(ocut)..
        alpha_iter(ocut) + sum(n, lambda_dsm_inv_iter(ocut,n)*(dsm_inv(n) - dsm_inv_iter(ocut,n))) + sum(n, lambda_scap_max_iter(ocut,n)*(Scap_max(n) -
scap_max_iter(ocut,n)) )
                      =L=     ALPHA
;

res_fcut(fcut)..
        beta_iter(fcut) + sum(n, gamma_dsm_inv_iter(fcut,n)*(dsm_inv(n) - dsm_inv_iter(fcut,n)) ) + sum(n, gamma_scap_max_iter(fcut,n)*(Scap_max(n) -
scap_max_iter(fcut,n)) )
                      =L=     0;

res_alpha_low..
        alpha_low       =L=     ALPHA
;

dsm_inv_fixed(n)..   dsm_inv(n) =l= %dsm_limit_per_node% ;

model master master problem
/
obj_M
res_ocut
res_fcut
res_alpha_low
dsm_inv_fixed
/
;


*------------------------------------ SUBPROBLEM -------------------------------

variables
COST_S              total cost sub problem
DELTA(t,n)            voltage angle difference
DSM(t,n)              demand-side management
;

positive variables
SCAP_MAX(n)               investment into storage capacity in kWh
DSM_INV(n)                investment into DSM capacity absolute number of meters
GEN(t,s,n)            generation of planttype s
GEN_WIND(t,n)      generation of wind
SIN(t,n)              storage input at time t and node n
SOUT(t,n)             storage output at time t and node n
;

equations
obj_s                 objective function
G_limit               Capacity limit of generation
G_wind_limit          Capacity limit for wind generation
Energybalance         Energy Balance
DSMlimit_upper        Maximum of (positive) demand-side management
DSMlimit_lower        Maximum of (negative) demand-side management
DSMbalance            Demand-side management balance over time
Spowerlimit_in        Storage input power limit
Spowerlimit_out       Storage output power limit
Slimit_lower          Maximum of (negative) storage management
Slimit_upper          Maximum of (positive) storage management
Sbalance              Storage in- and outflow balance over time
LF_limit_upper        Upper capacity limit of lineflow
LF_limit_lower        Lower capacity limit of lineflow
Slackbus              Delta at reference bus equals zero
res_dsm_inv_fix       restrition to keep dsm_inv fixed
res_scap_max_fix       restrition to keep scap_max fixed
;

*** COST
obj_s..          COST_S =e= sum((t,n), sum(s, g_c(s) * GEN(t,s,n)) + g_wind_c * GEN_WIND(t,n) + S_c * SOUT(t,n) ) ;

*** GENERATION
G_limit(t,s,n)..      0 =g=   GEN(t,s,n) - g_max(t,s,n);
G_wind_limit(t,n)..   0 =g=   GEN_WIND(t,n) - g_wind_max_scen(t,n);

* DEMAND-SIDE-MANAGEMENT
```

```
DSMlimit_upper(t,n).. 0 =g=   DSM(t,n) - dsm_inv(n) * dsm_max_pos(t,n) ;
DSMlimit_lower(t,n).. 0 =g=   DSM(t,n) - dsm_inv(n) * dsm_max_neg(t,n) ;
DSMbalance(n)..       0 =e=   sum(t, DSM(t,n));

* STORAGE
Spowerlimit_in(t,n)..  0 =g=   SIN(t,n)  - scap_max(n);
Spowerlimit_out(t,n).. 0 =g=   SOUT(t,n) - scap_max(n);
Slimit_lower(t,n)..    0 =g=   sum(tt$(ord(tt)<=ord(t)), Sout(tt,n)) - sum(tt$(ord(tt)<=ord(t)-1), Sin(tt,n) ) ;
Slimit_upper(t,n)..    0 =g=   sum(tt$(ord(tt)<=ord(t)), Sin(tt,n))  - sum(tt$(ord(tt)<=ord(t)-1), Sout(tt,n)) - Scap_max(n) ;
Sbalance(n)..          0 =e=   sum(t, SIN(t,n) * S_eff - SOUT(t,n));

*** ENERGY BALANCE
Energybalance(t,n)..  0 =e=   sum(s, GEN(t,s,n)) + GEN_WIND(t,n) + SOUT(t,n) - (q_ref_scen(t,n) + DSM(t,n) + SIN(t,n)) - sum(nn, b(n,nn) * DELTA(t,nn)) ;

*** GRID
*Transformerlimit(t,n)..  Transformer(n)   =g= q_ref(t,n)+DSM(t,n)+Sin(t,n)- sum(s,gen(n,t,s))  ;
LF_limit_upper(t,l).. 0 =g=   sum(n, h(l,n) * DELTA(t,n)) - lf_max(l) ;
LF_limit_lower(t,l).. 0 =g= - sum(n, h(l,n) * DELTA(t,n)) - lf_max(l) ;
Slackbus(t,n)..       0 =e=  slack(n) * DELTA(t,n) ;


res_dsm_inv_fix(n)..
        dsm_inv(n)           =E=     dsm_inv_fix(n)
;

res_scap_max_fix(n)..
        scap_max(n)          =E=     scap_max_fix(n)
;

model sub subproblem
/
obj_s,
*Transformerlimit,
G_limit,
G_wind_limit,
DSMlimit_upper,
DSMlimit_lower,
DSMbalance,
Spowerlimit_in,
Spowerlimit_out,
Slimit_lower,
Slimit_upper,
Sbalance,
Energybalance,
LF_limit_upper,
LF_limit_lower,
Slackbus,
res_dsm_inv_fix,
res_scap_max_fix
/
;


*--------------------------------- FEASIBILITY PROBLEM -------------------------------
Variable
        COST_F          feasibility objective
;

Positive Variable
        V           feasibility slack
;

equation
        obj_f           feasibility objective: min of slacks
        fres_mkt(t,n)     always feasible market clearing
;

obj_f..
        COST_F          =e=     V
;

fres_mkt(t,n)..
          0 =e=   sum(s, GEN(t,s,n)) + GEN_WIND(t,n) + SOUT(t,n) - (q_ref_scen(t,n) + DSM(t,n) + SIN(t,n)) - sum(nn, b(n,nn) * DELTA(t,nn)) + V
;

model fsub feasible subproblem
/
obj_f
fres_mkt,
*Transformerlimit,
G_limit,
G_wind_limit,
DSMlimit_upper,
DSMlimit_lower,
DSMbalance,
Spowerlimit_in,
```

```
Spowerlimit_out,
Slimit_lower,
Slimit_upper,
Sbalance,
LF_limit_upper,
LF_limit_lower,
Slackbus,
res_dsm_inv_fix,
res_scap_max_fix
/

;



*#####################################################################################
*                         DECOMPOSITION ALGORITHM
*#####################################################################################


option
*lp=cplex,
solprint=silent, limrow=0, limcol=0;
master.solvelink = 2;
sub.solvelink = 2;
option mip=bdmlp;

dsm_inv.fx('1')=0;

file out /output.txt/;
PUT out;
put "iter      COST_M    COST_S    alpha_low dsm_inv   scap_max  dual_dsm  dual_scap_max"/;


loop(iter$(not converged),

Scap_max.l('1') = 0;
Scap_max.l('2') = 0;
Scap_max.l('3') = 0;
Scap_max.l('4') = 0;
Scap_max.l('5') = 0;
DSM_inv.l('1') = 0;
DSM_inv.l('2') = 0;
DSM_inv.l('3') = 0;
DSM_inv.l('4') = 0;
DSM_inv.l('5') = 0;
SIN.fx('t24',n) = 0;


*      ********************
*      Solve master problem
*      ********************
       solve master using LP minimizing COST_M ;

*      Fix decision variables
       scap_max_fix(n) = scap_max.L(n);
       dsm_inv_fix(n) = dsm_inv.L(n);
       scap_max_iter(iter,n) = scap_max.L(n);
       dsm_inv_iter(iter,n) = dsm_inv.L(n);
       report_iter1(iter,"scap_max",n) = scap_max.L(n);
       report_iter1(iter,"dsm_inv",n) = dsm_inv.L(n);

*      Set lower bound
       iterlog("lower bound",iter) = COST_M.L;

*      ********************
*      Fesibility Check
*      ********************
       feasible = 0;
       loop(sc$(not feasible),

*             Assign respective scenario parameters
              q_ref_scen(t,n) =  q_ref(t,sc,n);
*              p_ref_scen(t) =  p_ref(t,sc);
*              DSM_max_pos_scen(t) =  DSM_max_pos(t,sc);
*              DSM_max_neg_scen(t) =  DSM_max_neg(t,sc);
              g_wind_max_scen(t,n) =  g_wind_max(t,sc,n);

              solve fsub using LP minimizing COST_F;

*             ********************
*             IF INFEASIBLE
*             ********************
              if(COST_F.L > 0,
*                    add feasibility cut
                     fcut(iter) = yes;
```

```
                beta_iter(iter) = COST_F.L;
                gamma_dsm_inv_iter(iter,n) = res_dsm_inv_fix.M(n);
                gamma_scap_max_iter(iter,n) = res_scap_max_fix.M(n);
*                end the iteration and goto master programm
                feasible = 1;
          );
     );

*     ********************
*     IF FEASIBLE
*     ********************
     if(feasible = 0,

*     ********************
*     Solve subproblem
*     ********************
          loop(sc,
*                Assign respective scenario parameters
                q_ref_scen(t,n) =  q_ref(t,sc,n);
*                p_ref_scen(t) =  p_ref(t,sc);
*                DSM_max_pos_scen(t) =  DSM_max_pos(t,sc);
*                DSM_max_neg_scen(t) =  DSM_max_neg(t,sc);
                g_wind_max_scen(t,n) =  g_wind_max(t,sc,n);

                solve sub using LP minimizing COST_S;

*               Assign cut parameters
                lambda_dsm_inv_scen(sc,n) = res_dsm_inv_fix.M(n);
                lambda_scap_max_scen(sc,n) = res_scap_max_fix.M(n);
                alpha_scen(sc) = COST_S.L;

*               Write reports
               report_iter2_DSM(iter,t,sc,n) = DSM.L(t,n);
               report_iter2_SIN(iter,t,sc,n) = SIN.L(t,n);
               report_iter2_SOUT(iter,t,sc,n) = SOUT.L(t,n);

     );

*     Add cut parameters
     ocut(iter)=yes;
     alpha_iter(iter) = sum(sc, prob(sc)* alpha_scen(sc));
     lambda_scap_max_iter(iter,n) = sum(sc, prob(sc)*lambda_scap_max_scen(sc,n));
     lambda_dsm_inv_iter(iter,n) = sum(sc, prob(sc)*lambda_dsm_inv_scen(sc,n));

*     Set upper bound
     iterlog("upper bound",iter) = alpha_iter(iter) + sum(n, scap_max.L(n) * scap_inv_cost + dsm_inv_cost * dsm_inv.L(n) ) ;

*      report_iter(iter,"Sin",t,sc) = Sin.L(t,sc);
*      report_iter(iter,"Sout",t,sc) = Sout.L(t,sc);
*      report_iter(iter,"DSM",t,sc) = DSM.L(t,sc);

*     ********************
*     Check convergence
*     ********************
     iterlog("error",iter) = iterlog("upper bound",iter) - iterlog("lower bound",iter);
     converged$(epsilon gt iterlog("error",iter)) = 1;


     put iter.tl:10:0," ",COST_M.L:10:3," ",COST_S.L:10:3," ", alpha_low:10:0," ";


put / ;

*     Add cut
*      uiter(iter) = yes;

  );

);


$ontext
* Report the final solution
report("stage1","Land",i) = X.L(i);
report(s,"Yield",i) = yield(i,s)*X.L(i);
report(s,"Purchases",i) = Y.L(i,s);
report(s,"Sold Normal",i) = W.L(i,s);
report(s,"Sold Quota",i) = Z.L(i,s);
report(s,"Sold Total",i) = Z.L(i,s) + W.L(i,s);
report("xxx","Profit","xxx") = -COST_M.L;
$offtext

lf(t,l) = sum(n, H(l,n) * delta.l(t,n) );
Q_tot(t,sc,n) = q_ref(t,sc,n) + DSM.l(t,n) + SIN.l(t,n) ;
Scap_max_total = sum(n, SCAP_MAX.l(n));
DSM_INV_total = sum(n, DSM_INV.l(n));
```

```
Gen_per_node(t,s)= sum(n,gen.l(t,s,n));
dem_per_node(t,sc)= sum(n,q_ref(t,sc,n));

DISPLAY COST_M.l, COST_S.l, prob, GEN.l, g_wind_max, GEN_WIND.l, q_ref, B, H, slack, lf, DSM.l, SIN.l, SOUT.l, SCAP_MAX.l, SCAP_MAX_total, DSM_INV.l, DSM_INV_total, Q_tot, delta.l, iterlog, alpha_iter, ALPHA.L, beta_iter, ocut, fcut, lambda_dsm_inv_iter, lambda_scap_max_iter, report_iter1, report_iter2_DSM, report_iter2_SIN, report_iter2_SOUT ;


*** Write zeros in EXCEL file
SIN.l(t,n)$(not SIN.l(t,n)) = eps;
SOUT.l(t,n)$(not SOUT.l(t,n)) = eps;
DSM.l(t,n)$(not DSM.l(t,n)) = eps;
lf(t,l)$(not lf(t,l)) = eps;
SCAP_MAX.l(n)$(not SCAP_MAX.l(n)) = eps;
DSM_INV.l(n)$(not DSM_INV.l(n)) = eps;
GEN_WIND.l(t,n)$(not GEN_WIND.l(t,n)) = eps;
Gen_per_node(t,s)$(not Gen_per_node(t,s)) = eps;
Dem_per_node(t,sc)$(not Dem_per_node(t,sc)) = eps;

*** Write output in EXCEL file
$libinclude xldump Dem_per_node output-smart-grid-stochastic.xls Dem!b3
$libinclude xldump GEN_WIND.l output-smart-grid-stochastic.xls GEN_WIND!b3
$libinclude xldump Gen_per_node output-smart-grid-stochastic.xls gen!b3
$libinclude xldump Sin.l output-smart-grid-stochastic.xls Sin!b3
$libinclude xldump Sout.l output-smart-grid-stochastic.xls Sout!b3
$libinclude xldump lf output-smart-grid-stochastic.xls lf!b3
$libinclude xldump SCAP_MAX.l output-smart-grid-stochastic.xls INVEST!b3
$libinclude xldump DSM_INV.l output-smart-grid-stochastic.xls INVEST!b6
$libinclude xldump q_ref output-smart-grid-stochastic.xls demand!b3
$libinclude xldump DSM.l output-smart-grid-stochastic.xls DSM!b3
$libinclude xldump S_eff output-smart-grid-stochastic.xls INVEST!b9
```

GAMS Code of the model in Chapter 3

```
*================================================================================
* Andreas Schröder 31 Juli 2011
* Model Esymmetry (Traber, Kemfert 2011) applied to E-Mobility
* Model run requires access to the file "Input_esymmetry2011.xls"
*================================================================================

option mcp = path;
option iterlim = 100000;

set
f        Firm        /DE_Eon,DE_EnBW,DE_RWE,DE_Vattenfall,DE_Dummy/
t        Period      /1*168/
n        Technology  /HYD,NUC_L,NUC_S,BC_New,HC_New,BC_Old,HC_Old,NG_CC,NG_ST,NG_GT,O_ST,O_GT/
nash(f)         Firmen die sich nach Nash verhalten;
nash(f):=no;
nash("DE_Dummy")        = no ;
nash("DE_RWE")          = yes ;
nash("DE_Eon")          = yes  ;
nash("DE_Vattenfall")   = yes  ;
nash("DE_Enbw")         = yes  ;

scalar nash1            Unterdrueckt Nash-Verhalten von Firmen        /0/ ;
alias (f,ff);

parameter
q_max(f,n)     Installed capacity of firm f and technology n
s(n)           Start-up fuel requirement
dq_max(n)      Maximum load gradient
MSD(n)         marginal start up depreciation
p_f(n)         fuel cost of tech n  in cent pro kwh
emf(n)         emissions factor
eta(n)         degree of efficiency of tech n
oc(n)          operating cost of tech n in t
a(n)           availability of technology n
phi            emission price in cent per kg CO2  /2.5/
maxGrad(f,n)
sigma(t)       Periodic price elasticity of demand
;

Scalar EV_scaling scaling of EV vehicles profile to yield MW used - 1 corresponds to 1000 EV /50/;
Parameter EV_profile(t) kW demand profile of a fast charging station dispatching 35 kWh a week thus equivalent to the weekly use of one car. Source: Barnes (2008)
/
1    0.032
2    0.027
3    0.038
4    0.065
5    0.113
```

```
6	0.172
7	0.232
8	0.291
9	0.329
10	0.334
11	0.350
12	0.372
13	0.393
14	0.410
15	0.420
16	0.399
17	0.367
18	0.302
19	0.226
20	0.172
21	0.140
22	0.097
23	0.065
24	0.043
25	0.048
26	0.024
27	0.029
28	0.053
29	0.087
30	0.135
31	0.188
32	0.245
33	0.322
34	0.366
35	0.375
36	0.371
37	0.356
38	0.351
39	0.337
40	0.322
41	0.289
42	0.250
43	0.197
44	0.159
45	0.120
46	0.091
47	0.058
48	0.039
49	0.015
50	0.025
51	0.050
52	0.111
53	0.181
54	0.227
55	0.262
56	0.272
57	0.292
58	0.343
59	0.363
60	0.378
61	0.373
62	0.368
63	0.353
64	0.338
65	0.297
66	0.242
67	0.186
68	0.141
69	0.101
70	0.060
71	0.035
72	0.025
73	0.014
74	0.019
75	0.052
76	0.113
77	0.179
78	0.231
79	0.259
80	0.273
81	0.268
82	0.278
83	0.282
84	0.301
85	0.306
86	0.334
87	0.348
88	0.339
89	0.320
90	0.254
91	0.188
```

```
92      0.132
93      0.099
94      0.056
95      0.038
96      0.024
97      0.019
98      0.024
99      0.053
100     0.120
101     0.192
102     0.235
103     0.269
104     0.283
105     0.273
106     0.278
107     0.283
108     0.297
109     0.307
110     0.331
111     0.345
112     0.340
113     0.326
114     0.264
115     0.192
116     0.144
117     0.101
118     0.058
119     0.038
120     0.024
121     0.020
122     0.025
123     0.055
124     0.125
125     0.200
126     0.245
127     0.280
128     0.295
129     0.285
130     0.290
131     0.295
132     0.310
133     0.320
134     0.345
135     0.360
136     0.355
137     0.340
138     0.275
139     0.200
140     0.150
141     0.105
142     0.060
143     0.040
144     0.025
145     0.021
146     0.026
147     0.058
148     0.131
149     0.210
150     0.257
151     0.294
152     0.310
153     0.299
154     0.305
155     0.310
156     0.326
157     0.336
158     0.362
159     0.378
160     0.373
161     0.357
162     0.289
163     0.210
164     0.158
165     0.110
166     0.063
167     0.042
168     0.026
/
;

Parameter EV(t) EV load aggregated;
EV(t) = EV_profile(t)*EV_scaling;

Parameter D0(t) Reference residual demand in MW
/
1       42040
```

2	40797
3	40055
4	40149
5	41089
6	42876
7	48529
8	54265
9	56798
10	57116
11	57589
12	58344
13	57611
14	56863
15	55838
16	55131
17	54687
18	55604
19	56491
20	56305
21	54201
22	51621
23	49055
24	44879
25	41576
26	40271
27	39602
28	39637
29	40545
30	42325
31	47568
32	52972
33	55411
34	55913
35	56469
36	57303
37	56714
38	55879
39	54909
40	54292
41	53973
42	54902
43	55782
44	55799
45	53918
46	51516
47	48961
48	44761
49	42188
50	40790
51	40036
52	39849
53	40753
54	42565
55	47547
56	52831
57	55387
58	55944
59	56569
60	57253
61	56450
62	54788
63	53212
64	52378
65	52340
66	53541
67	54061
68	53471
69	51295
70	49039
71	47288
72	43767
73	40203
74	38377
75	37383
76	37349
77	37578
78	37417
79	37679
80	39818
81	42949
82	45450
83	46653
84	47296
85	46383
86	44591
87	42992

```
88      42369
89      42728
90      44677
91      46103
92      46058
93      44023
94      42381
95      41574
96      38778
97      35938
98      34211
99      33580
100     33268
101     33419
102     33140
103     32804
104     33778
105     35942
106     38082
107     39927
108     42005
109     41688
110     39926
111     38455
112     37849
113     38422
114     40673
115     42897
116     43618
117     43129
118     42327
119     42172
120     39230
121     36704
122     35739
123     35528
124     35798
125     37001
126     39340
127     45795
128     52141
129     55311
130     56217
131     57107
132     58089
133     57548
134     56791
135     55639
136     54861
137     54255
138     55118
139     55746
140     55681
141     53891
142     51534
143     49022
144     44751
145     41570
146     40295
147     39792
148     39833
149     40874
150     42839
151     48636
152     54573
153     57367
154     57725
155     58093
156     58895
157     58254
158     57487
159     56499
160     55823
161     55300
162     56150
163     56823
164     56683
165     54710
166     52217
167     49608
168     45264
/
;

Parameter P0(t)  Reference price in ct per kWh
/
```

1	*3.72*
2	*3.49*
3	*3.17*
4	*2.89*
5	*2.97*
6	*3.54*
7	*4.40*
8	*5.32*
9	*5.52*
10	*5.60*
11	*5.71*
12	*5.83*
13	*5.60*
14	*5.43*
15	*5.24*
16	*5.07*
17	*5.00*
18	*5.41*
19	*5.70*
20	*5.63*
21	*5.16*
22	*4.68*
23	*4.61*
24	*4.14*
25	*3.92*
26	*3.63*
27	*3.33*
28	*3.08*
29	*3.10*
30	*3.66*
31	*4.48*
32	*5.42*
33	*5.71*
34	*5.70*
35	*5.67*
36	*5.75*
37	*5.51*
38	*5.31*
39	*5.08*
40	*4.93*
41	*5.00*
42	*5.36*
43	*5.70*
44	*5.57*
45	*5.13*
46	*4.78*
47	*4.71*
48	*4.16*
49	*3.82*
50	*3.49*
51	*3.27*
52	*2.98*
53	*3.15*
54	*3.58*
55	*4.38*
56	*5.29*
57	*5.68*
58	*5.83*
59	*5.89*
60	*5.97*
61	*5.68*
62	*5.31*
63	*5.03*
64	*4.81*
65	*4.82*
66	*5.29*
67	*5.55*
68	*5.32*
69	*4.95*
70	*4.60*
71	*4.68*
72	*4.31*
73	*4.15*
74	*3.76*
75	*3.45*
76	*3.16*
77	*3.05*
78	*3.08*
79	*3.12*
80	*3.65*
81	*4.09*
82	*4.56*
83	*4.73*
84	*4.82*
85	*4.73*
86	*4.34*

```
87     4.08
88     3.98
89     4.07
90     4.57
91     5.08
92     5.01
93     4.47
94     4.24
95     4.46
96     3.98
97     3.51
98     3.08
99     2.72
100     2.27
101     2.16
102     2.00
103     1.63
104     2.02
105     2.85
106     3.41
107     3.71
108     4.08
109     4.07
110     3.44
111     3.13
112     2.93
113     3.03
114     3.81
115     4.58
116     4.81
117     4.70
118     4.47
119     4.65
120     3.96
121     3.59
122     3.10
123     2.80
124     2.37
125     2.43
126     3.04
127     4.62
128     5.44
129     5.66
130     5.76
131     5.83
132     6.04
133     5.74
134     5.58
135     5.36
136     5.14
137     5.04
138     5.53
139     5.75
140     5.59
141     5.12
142     4.67
143     4.62
144     4.12
145     3.85
146     3.54
147     3.29
148     3.02
149     3.17
150     3.74
151     4.50
152     5.42
153     5.81
154     5.84
155     5.87
156     6.05
157     5.74
158     5.60
159     5.40
160     5.19
161     5.18
162     5.61
163     5.85
164     5.65
165     5.12
166     4.72
167     4.65
168     4.16
/
;

Parameter
```

```
TC_t(f,t) cost
TP_t(f,t) profit
;

$libinclude xlimport sigma   .\Input_esymmetry2011.xls a15:fl16
$libinclude xlimport p_f   .\Input_esymmetry2011.xls    b23:m24
$libinclude xlimport eta   .\Input_esymmetry2011.xls   b27:m28
$libinclude xlimport oc   .\Input_esymmetry2011.xls    b31:m32
$libinclude xlimport q_max   .\Input_esymmetry2011.xls    a35:m40
$libinclude xlimport s   .\Input_esymmetry2011.xls    b43:m44
$libinclude xlimport dq_max  .\Input_esymmetry2011.xls    b47:m48
$libinclude xlimport emf  .\Input_esymmetry2011.xls    b51:m52
$libinclude xlimport MSD  .\Input_esymmetry2011.xls    b55:m56
$libinclude xlimport a  .\Input_esymmetry2011.xls    b58:m59

positive variables
P(t)               Price in period t
TC             Total Costs
TSC(f,n,t)             Total Startupcosts
TP             Total profit
MSC(f,n,t)          Marginal start up costs
MSE(f,n,t)          Marginal start up emissions
MC(n)             Marginal Costs
ME(n)             Marginal Emissions
q(f,n,t)              Production
e                 Emissions
DIMq(f,n,t)              stictly positive Production
dq(f,n,t)              Load gradient
lambda(f,n,t)        Shadow price of startup restriction
kappa(f,n,t)        Shadow price of capacity restriction
theta(f,t)           Market share
markup(f,t)           Mark-up
;

scalar scaling_cost  /1/;

equations
profit(f,n,t)
market(t)
market_share(f,t)
mark_up(f,t)
marginal_costs(n)
marginal_emissions(n)
marginal_startupcosts(f,n,t)
marginal_startupemissions(f,n,t)
startup_restriction(f,n,t)
load_gradient(f,n,t)
capacity_restriction(f,n,t)
total_costs(f)
startupcosts(f,n,t)
total_emissions
total_profit(f)
;

profit(f,n,t)..
MC(n)+phi*ME(n)+lambda(f,n,t)+kappa(f,n,t)
=e=
P(t)*(1-(theta(f,t)/sigma(t))$(nash1*nash(f)))+lambda(f,n,t+1)
;

market(t)..
sum(n,sum(f,q(f,n,t))) =e=  EV(t) + D0(t)* (P(t)/P0(t))**(-sigma(t))
;

market_share(f,t)$(nash(f)*nash1)..
theta(f,t)*sum(ff,sum(n,q(ff,n,t)))=e= sum(n,q(f,n,t))
;

mark_up(f,t)$(nash(f)*nash1)..
markup(f,t)=e=P(t)*theta(f,t)/sigma(t)
;

marginal_costs(n)..
MC(n)=e=   scaling_cost*( p_f(n)/(eta(n)+0.000001)+oc(n) )
;

marginal_emissions(n)..
ME(n)=e= scaling_cost*( emf(n)/(eta(n)+0.000001) )
;

marginal_startupcosts(f,n,t)..
MSC(f,n,t)=e= scaling_cost*(  p_f(n)*s(n)+MSD(n))
;

marginal_startupemissions(f,n,t)..
MSE(f,n,t)=e= scaling_cost*( emf(n)*s(n) )
```

```
;

capacity_restriction(f,n,t)..
q_max(f,n)*a(n)=g=q(f,n,t)
;

startup_restriction(f,n,t)$((ord(t) >= 2) or (ord(t)<card(t)))..
dq_max(n)*q_max(f,n)=g=dq(f,n,t)
;

load_gradient(f,n,t)..
dq(f,n,t)=e=q(f,n,t)-q(f,n,t-1)
;

total_costs(f)..

TC(f)=e=sum(t,sum(n,q(f,n,t)*(MC(n)+phi*ME(n))+dq(f,n,t)*(MSC(f,n,t)+phi*MSE(f,n,t))))
;
total_profit(f)..

TP(f)=e= sum(t,sum(n,P(t)*q(f,n,t)))-TC(f)
;
total_emissions..
e =e= sum(f,sum(n$(eta(n)),sum(t,q(f,n,t)*emf(n)/eta(n)+ s(n)*emf(n)*dq(f,n,t))))
;
startupcosts(f,n,t)..
TSC(f,n,t)=e= dq(f,n,t)*(MSC(f,n,t)+phi*MSE(f,n,t))
*sum(t,sum(n,dq(f,n,t)*(MSC(f,n,t)+phi*MSE(f,n,t))))
;

model   esymmetry2011 /profit.q,market.p,market_share.theta,mark_up.markup
marginal_costs.MC,marginal_emissions.ME,capacity_restriction.kappa,
marginal_startupcosts.MSC,marginal_startupemissions.MSE,load_gradient.dq, startup_restriction.lambda,
total_costs.TC,startupcosts.TSC,total_profit.TP,total_emissions.e /;

P.l(t):=7;
*MSC.lo(f,n,t):=0.000000001;
kappa.lo(f,n,t):=0.00000001;
* Fixing ramping variables:
lambda.fx(f,n,t)$( (ORD(t)=1) or (ord(t) ne card(t)) ) = 0 ;

solve esymmetry2011 using mcp;
DIMq.l(f,n,t):=q.l(f,n,t)+0.000000001;

*$libinclude xldump e.l      .\esymmetry2011Comp.xls Total_Emissions_e
*$libinclude xldump TC.l      .\esymmetry2011Comp.xls Total_Costs_TC
*$libinclude xldump TP.l      .\esymmetry2011Comp.xls Total_Profit_TP
*$libinclude xldump DIMq.l      .\esymmetry2011Comp.xls Production_q
*$libinclude xldump lambda.l      .\esymmetry2011Comp.xls shadow_price_startup_lamda
*$libinclude xldump TSC.l      .\esymmetry2011Comp.xls Total_Startup_Costs_TSC
*$libinclude xldump MC.l      .\esymmetry2011Comp.xls Marginal_Costs_MC
*$libinclude xldump markup.l      .\esymmetry2011Comp.xls Share_Theta
*$libinclude xldump p.l      .\esymmetry2011Comp.xls Price_P
*$libinclude xldump kappa.l      .\esymmetry2011Comp.xls shadow_price_capacity_kappa
*$libinclude xldump EV      .\esymmetry2011Comp.xls EV

****************


nash1:=0;

solve esymmetry2011 using mcp;

maxGrad(f,n):=dq_max(n)*q_max(f,n);
TC_t(f,t)=sum(n,Q.l(f,n,t)*(MC.l(n)+phi*ME.l(n))+dq.l(f,n,t)*(MSC.l(f,n,t)+phi*MSE.l(f,n,t)))    ;
TP_t(f,t)= sum(n,P.l(t)*Q.l(f,n,t))-TC_t(f,t)    ;

DIMq.l(f,n,t):=q.l(f,n,t)+0.000000001;
$libinclude xldump e.l      .\esymmetry2011Nash.xls Total_Emissions_e
$libinclude xldump TC.l      .\esymmetry2011Nash.xls Total_Costs_TC
$libinclude xldump TP.l      .\esymmetry2011Nash.xls Total_Profit_TP
$libinclude xldump TC_t      .\esymmetry2011Nash.xls Total_Costs_TC_t
$libinclude xldump TP_t      .\esymmetry2011Nash.xls Total_Profit_TP_t
$libinclude xldump DIMq.l      .\esymmetry2011Nash.xls Production_q
$libinclude xldump lambda.l      .\esymmetry2011Nash.xls shadow_price_startup_lamda
$libinclude xldump TSC.l      .\esymmetry2011Nash.xls Total_Startup_Costs_TSC
*$libinclude xldump MSC.l      .\esymmetry2011Nash.xls Marginal_Startup_Costs_MSC
$libinclude xldump markup.l      .\esymmetry2011Nash.xls Mark_up
$libinclude xldump p.l      .\esymmetry2011Nash.xls Price_P
$libinclude xldump kappa.l      .\esymmetry2011Nash.xls Shadow_price_capacity_Kappa
$libinclude xldump EV      .\esymmetry2011Nash.xls EV
```

GAMS Code of the model in Chapter 4

```
*===================================================================================
* Combined Power Plant Investment and Electricity Dispatch Model – November 2011 - Andreas Schroeder
*===================================================================================

option mcp = path;
option reslim = 12000;
*option iterlim = 100000;

$eolcom #
* this sets # as end-of-line comment (text after # will be ignored by GAMS)

set
f           Firm   /DE_Eon,DE_EnBW,DE_RWE,DE_Vattenfall,DE_Dummy/
t           Period  /1*12/
n           Technology /HYD,NUCL,HC_New,BC_Old,HC_Old,NG_CC,NG_ST,NG_GT,O_ST,O_GT,CC_New,NG_GT_New,HC_Retro/
year        period of years /2010,2015,2020,2025,2030,2035/
a           scenario /s0*s15/
A_Matrix(a,a)       Ancestor-successor node mapping in scenario tree / s0.s1, s1.(s2*s3), s2.(s4*s5),
s3.(s5*s7),s4.s8,s5.s9,s6.s10,s7.s11,s8.s12,s9.s13,s10.s14,s11.s15/
Ancestor_Matrix(a,a)     Ancestor node mapping in scenario tree / s0.s1, s1.s2,
s1.s3,(s1,s2).s4,(s1,s2).s5,(s1,s3).s6,(s1,s3).s7,(s1,s2,s4).s8,(s1,s2,s5).s9,(s1,s3,s6).s10,(s1,s3,s7).s11,(s1,s2,s4,s8).s12,(s1,s2,s5,s9).s13,(s1,s3,s6,s10).s14,(s1,s3,s
7,s11).s15/
P_Matrix(year,a)    Mapping of scenario node to time period / 2010.s0, 2015.s1, 2020.(s2*s3), 2025.(s4*s7), 2030.(s8*s11), 2030.(s12*s15)/
nash(f)       Firmen die sich nach Nash verhalten;
nash(f):=no;
nash("DE_Dummy")          = no ;
nash("DE_RWE")            = yes ;
nash("DE_Eon")            = yes  ;
nash("DE_Vattenfall")     = yes  ;
nash("DE_Enbw")           = yes  ;

Alias (a,aa) ;

scalar nash1 Unterdrueckt Nash-Verhalten von Firmen wenn null        /0/ ;
Parameter scaling_kw scaling from GW to kW /1/;
scalar scaling_cost  /1/; #Scaling of prices and costs from kWh to GWh ct to EUR
Parameter weeks(a) weeks per period a;
weeks(a) = 8760/card(t)*5;
weeks('s12') = 8760/card(t)*15;
weeks('s13') = 8760/card(t)*15;
weeks('s14') = 8760/card(t)*15;
weeks('s15') = 8760/card(t)*15;

alias (f,ff), (a,aa);

parameter
q_max(f,n,a)      Installed capacity of firm f and technology n
s(n)              Start-up fuel requirement
dq_max(n)         Maximum load gradient
MSD(n)            Marginal start up depreciation
p_f(n,a)          Fuel cost of tech n  in cent pro kwh
emf(n)            Emissions factor
eta(n)            Degree of efficiency of tech n
oc(n)             Operating cost of tech n in t
available(n)      Availability of technology n
MC(n,a)           Marginal cost of generation
MSC(n,a)          Marginal start up costs
MSE(n)            Marginal start up emissions
ME(n)             Marginal Emissions
*TP(f,a)          Total profit
*TC(f,a)          Total Costs
TSC(f,n,t,a)      Total Startupcosts
E(a)              Emissions
TP(f,a)           Revenue - Cost = Total Profit
Expected_profits(f) TP multiplied by their probabilities
TC(f,a)           Total Costs
TRev(f,a)         Total revenues
TQ_tech(t,a,n)    Total non-renewable production over all firms
TQ_tech_s1(t,n)   Total generation in scenario s1
TQ(t,a)           Total non-renewable production over all firms and technologies
FullLoadHour(n,a)   Full load hours per technology and year
AveragePrice(a)     Average prices per year
Renewable_share(a)  Share of renewable energy in overall production
Yearly_demand(a)    Yearly demand in TWh
sigma(t)          Periodic price elasticity of demand
;

Parameter yearnumber(a)
/
s0     2010
s1     2015
s2     2020
```

```
s3      2020
s4      2025
s5      2025
s6      2025
s7      2025
s8      2030
s9      2030
s10     2030
s11     2030
s12     2035
s13     2035
s14     2035
s15     2035
/
;

Parameter      discount(a)      discount factor
$ontext
/
s1    0.85
s2    0.56
s3    0.56
s4    0.37
s5    0.37
s6    0.37
s7    0.37
s8    0.24
s9    0.24
s10   0.24
s11   0.24
s12   0.16
s13   0.16
s14   0.16
s15   0.16
/
$offtext
;
discount(a)=1;

Parameter q_min(a) Requirement of minimum reserve capacity in MW imposed by system operator
/
s0    0
s1    500
s2    1000
s3    1000
s4    1500
s5    1500
s6    1500
s7    1500
s8    2000
s9    2000
s10   2000
s11   2000
s12   3000
s13   3000
s14   3000
s15   3000
/
;
q_min(a)=0;

Table q_max_2010(f,n) Maximum capacity for generation in MW.
              HYD       NUCL      HC_Old    BC_Old    NG_CC     NG_ST     NG_GT     O_ST      O_GT      CC_New   NG_GT_New  HC_Retro
DE_Eon          1507      6999      8482      866       1212      2806      1244      815       24        0         0
DE_EnBW         427       4311      3171      872       552       317       409       1         227       0         0
DE_RWE          638       5465      4776      9463      2044      3457      808       33        232       0         0
DE_Vattenfall   1000      1461      1195      7451      734       423       922       259       557       0         0
DE_Dummy        893       1992      7458      531       4430      2746      3728      749       1200      0         0
;

Table q_max_2015(f,n) Maximum capacity for generation in MW.
              HYD       NUCL      HC_Old    BC_Old    NG_GT     NG_ST     NG_CC     O_ST      O_GT      CC_New      NG_GT_New  HC_Retro
DE_Eon          1507      4594      5052      866       803       723       1212      42        24
DE_EnBW         427       2636      3101      872       118       102       552       1         120
DE_RWE          638       3058      3330      1853      637       397       2044      32        2
DE_Vattenfall   1000      947       945       7451      605       0         734       80        277
DE_Dummy        893       1985      5875      531       3397      1920      4430      468       324
;

Table q_max_2020(f,n) Maximum capacity for generation in MW.
              HYD       NUCL      HC_Old    BC_Old    NG_GT     NG_ST     NG_CC     O_ST      O_GT      CC_New      NG_GT_New   HC_Retro
DE_Eon          1507      3319      2914      863       215       101       1212      42        5
DE_EnBW         427       1278      3078      872       78        13        552       0         0
DE_RWE          638       2095      3137      1232      570       37        2044      32        2
DE_Vattenfall   1000      947       945       7312      605       0         734       0         0
DE_Dummy        893       1664      4375      502       2883      1615      4430      273       244
```

```
;

Table q_max_2025(f,n) Maximum capacity for generation in MW.
              HYD     NUCL   HC_Old   BC_Old   NG_GT   NG_ST   NG_CC   O_ST   O_GT   CC_New   NG_GT_New   HC_Retro
DE_Eon        1507    0      1957     533      211     77      1212    42     0
DE_EnBW       427     0      772      872      77      0       552     0      0
DE_RWE        638     0      764      1232     414     22      2044    32     0
DE_Vattenfall 1000    0      945      5488     270     0       734     0      0
DE_Dummy      893     0      2291     397      2299    1237    4430    273    233
;

Table q_max_2030(f,n) Maximum capacity for generation in MW.
              HYD     NUCL   HC_Old   BC_Old   NG_GT   NG_ST   NG_CC   O_ST   O_GT   CC_New   NG_GT_New   HC_Retro
DE_Eon        1507    0      638      533      211     74      1212    42     0
DE_EnBW       427     0      762      872      77      0       552     0      0
DE_RWE        638     0      394      1074     414     20      2044    32     0
DE_Vattenfall 0       0      289      4560     0       0       734     0      0
DE_Dummy      893     0      942      364      2023    566     4331    273    120
;

Table q_max_2035(f,n) Maximum capacity for generation in MW.
              HYD     NUCL   HC_Old   BC_Old   NG_GT   NG_ST   NG_CC   O_ST   O_GT   CC_New   NG_GT_New   HC_Retro
DE_Eon        1507    0      116      533      31      14      1114    0      0
DE_EnBW       427     0      355      865      72      0       384     0      0
DE_RWE        638     0      69       905      225     15      2044    0      0
DE_Vattenfall 0       0      0        3629     0       0       679     0      0
DE_Dummy      893     0      320      338      780     483     3869    218    21
;

Table q_max_2040(f,n) Maximum capacity for generation in MW.
              HYD     NUCL   HC_Old   BC_Old   NG_GT   NG_ST   NG_CC   O_ST   O_GT   CC_New   NG_GT_New   HC_Retro
DE_Eon        1507    0      0        0        28      14      827     0      0
DE_EnBW       427     0      0        0        0       0       0       0      0
DE_RWE        638     0      0        905      138     14      1160    0      0
DE_Vattenfall 0       0      0        0        0       0       299     0      0
DE_Dummy      893     0      0        0        85      350     2072    0      0
;

q_max(f,n,'s0') = scaling_kw*q_max_2010(f,n);
q_max(f,n,'s1') = scaling_kw*q_max_2015(f,n);
q_max(f,n,'s2') = scaling_kw*q_max_2020(f,n);
q_max(f,n,'s3') = scaling_kw*q_max_2020(f,n);
q_max(f,n,'s4') = scaling_kw*q_max_2025(f,n);
q_max(f,n,'s5') = scaling_kw*q_max_2025(f,n);
q_max(f,n,'s6') = scaling_kw*q_max_2025(f,n);
q_max(f,n,'s7') = scaling_kw*q_max_2025(f,n);
q_max(f,n,'s8') = scaling_kw*q_max_2030(f,n);
q_max(f,n,'s9') = scaling_kw*q_max_2030(f,n);
q_max(f,n,'s10') = scaling_kw*q_max_2030(f,n);
q_max(f,n,'s11') = scaling_kw*q_max_2030(f,n);
q_max(f,n,'s12') = scaling_kw*q_max_2035(f,n);
q_max(f,n,'s13') = scaling_kw*q_max_2035(f,n);
q_max(f,n,'s14') = scaling_kw*q_max_2035(f,n);
q_max(f,n,'s15') = scaling_kw*q_max_2035(f,n);


parameter investment_cost(n)      Construction cost of a new plant in ct per kW
/
HYD       100000000
NUCL      330000
HC_New    130000
BC_Old    170000
HC_Old    130000
NG_CC     65000
NG_ST     60000
NG_GT     50000
O_ST      60000
O_GT      50000
CC_New    70000
NG_GT_New 50000
HC_Retro  110000
/
;

Parameter available(n) availabilitiy of plant in per cent of time
/
HYD       0.75
NUCL      0.86
HC_New    1
BC_Old    0.82
HC_Old    0.82
NG_CC     0.86
NG_ST     0.86
NG_GT     0.86
O_ST      0.84
O_GT      0.84
```

```
CC_New    0.9
NG_GT_New 0.9
HC_Retro  1
/
;

Parameter MSD(n) marginal start-up or ramping depreciation cost in ct per kW
/
HYD       0
NUCL      0.17
HC_New    0.5
BC_Old    0.1
HC_Old    0.15
NG_CC     1
NG_ST     1
NG_GT     1
O_ST      0.5
O_GT      0.5
CC_New    1
NG_GT_New 1
HC_Retro  0.5
/
;

Parameter emf(n) emission factor in kg per kWh
/
HYD       0
NUCL      0
HC_New    0.34
BC_Old    0.4
HC_Old    0.34
NG_CC     0.2
NG_ST     0.2
NG_GT     0.2
O_ST      0.28
O_GT      0.28
CC_New    0.2
NG_GT_New 0.2
HC_Retro  0.36
/
;

Parameter dq_max(n)  start-up or ramping limit in per cent
/
HYD       1
NUCL      0.15
HC_New    0.5
BC_Old    0.4
HC_Old    0.4
NG_CC     0.5
NG_ST     0.36
NG_GT     1
O_ST      0.36
O_GT      1
CC_New    0.55
NG_GT_New 1
HC_Retro  0.4
/
;

dq_max(n) = dq_max(n)*2;

Parameter s(n)    start-up or ramping fuel requirement in kWh per kW

/
HYD       0
NUCL      16.7
HC_New    6.2
BC_Old    6.2
HC_Old    6.2
NG_CC     3.5
NG_ST     4.0
NG_GT     1.1
O_ST      4.0
O_GT      1.1
CC_New    2.9
NG_GT_New 1.1
HC_Retro  6.2
/
;

Parameter eta(n)   efficiency in per cent
/
HYD       1
NUCL      0.34
HC_New    0.43
```

```
BC_Old    0.38
HC_Old    0.34
NG_CC     0.56
NG_ST     0.4
NG_GT     0.35
O_ST      0.38
O_GT      0.33
CC_New    0.6
NG_GT_New 0.47
HC_Retro  0.38
/
;

Parameter oc(n) variable operation cost in ct per kWh
/
HYD       0.26
NUCL      0.04
HC_New    0.2
BC_Old    0.26
HC_Old    0.2
NG_CC     0.13
NG_ST     0.15
NG_GT     0.15
O_ST      0.15
O_GT      0.15
CC_New    0.13
NG_GT_New 0.15
HC_Retro  0.1
/
;


Table p_f(n,a)     fuel price in ct per kWh
*IEA (2011) Scenarios with 15 scenarios
            s0    s1    s2    s3    s4    s5    s6    s7    s8    s9    s10   s11   s12   s13   s14   s15
HYD         0.00  0.00  0.00  0.00  0.00  0.00  0.00  0.00  0.00  0.00  0.00  0.00  0.00  0.00  0.00  0.00
NUCL        0.80  0.80  0.80  0.80  0.80  0.80  0.80  0.80  0.80  0.80  0.80  0.80  0.80  0.80  0.80  0.80
HC_New      0.65  0.67  0.60  0.70  0.54  0.71  0.71  0.73  0.47  0.72  0.72  0.76  0.45  0.73  0.73  0.77
BC_Old      0.29  0.32  0.32  0.32  0.33  0.33  0.33  0.33  0.34  0.34  0.34  0.34  0.34  0.34  0.34  0.34
HC_Old      0.65  0.67  0.60  0.70  0.54  0.71  0.71  0.73  0.47  0.72  0.72  0.76  0.45  0.73  0.73  0.77
NG_CC       1.66  2.13  2.44  2.30  2.64  2.46  2.46  2.17  2.79  2.59  2.59  2.15  2.88  2.68  2.68  2.08
NG_ST       1.66  2.13  2.44  2.30  2.64  2.46  2.46  2.17  2.79  2.59  2.59  2.15  2.88  2.68  2.68  2.08
NG_GT       1.66  2.13  2.44  2.30  2.64  2.46  2.46  2.17  2.79  2.59  2.59  2.15  2.88  2.68  2.68  2.08
O_ST        3.02  3.94  4.57  4.20  4.92  4.39  4.39  3.75  5.20  4.54  4.54  3.75  5.41  4.64  4.64  3.75
O_GT        3.02  3.94  4.57  4.20  4.92  4.39  4.39  3.75  5.20  4.54  4.54  3.75  5.41  4.64  4.64  3.75
CC_New      1.66  2.13  2.44  2.30  2.64  2.46  2.46  2.17  2.79  2.59  2.59  2.15  2.88  2.68  2.68  2.08
NG_GT_New   1.66  2.13  2.44  2.30  2.64  2.46  2.46  2.17  2.79  2.59  2.59  2.15  2.88  2.68  2.68  2.08
HC_Retro    0.65  0.67  0.60  0.70  0.54  0.71  0.71  0.73  0.47  0.72  0.72  0.76  0.45  0.73  0.73  0.77
;

Table  sv(n,a) Exogenous salvage value in ct with fixed full-load hours
            s0    s1     s2     s3     s4     s5     s6     s7     s8     s9     s10    s11    s12    s13    s14    s15
HYD         0     0      0      0      0      0      0      0      0      0      0      0      0      0      0      0
NUCL        0     0      0      0      0      0      0      0      0      0      0      0      0      0      0      0
HC_New      7867  13052  16469  16469  18721  18721  18721  18721  20973  20973  20973  20973  22579  22579  22579  22579
BC_Old      4683  7770   9804   9804   11839  11839  11839  11839  13873  13873  13873  13873  15907  15907  15907  15907
HC_Old      4594  7621   9617   9617   11612  11612  11612  11612  13607  13607  13607  13607  15603  15603  15603  15603
NG_CC       0     0      5377   5377   8922   8922   8922   8922   11257  11257  11257  11257  11725  11725  11725  11725
NG_ST       0     0      0      0      0      0      0      0      0      0      0      0      0      0      0      0
NG_GT       0     0      0      0      0      0      0      0      0      0      0      0      0      0      0      0
O_ST        0     0      0      0      0      0      0      0      0      0      0      0      0      0      0      0
O_GT        0     0      0      0      0      0      0      0      0      0      0      0      0      0      0      0
CC_New      0     0      5781   5781   9592   9592   9592   9592   12103  12103  12103  12103  12606  12606  12606  12606
NG_GT_New   0     0      4714   4714   7820   7820   7820   7820   9868   9868   9868   9868   10277  10277  10277  10277
HC_Retro    0     0      0      0      0      0      0      0      4158   4158   4158   4158   8316   8316   8316   8316
;
sv(n,a)=0;


Parameter phi(a) emission price in ct per kg (IEA 2011)
/
s0     2.00
s1     2.50
s2     3.00
s3     4.50
s4     3.50
s5     3.50
s6     3.50
s7     7.50
s8     4.00
s9     4.00
s10    4.00
s11    9.50
s12    4.50
s13    4.50
s14    4.50
```

```
s15      12.00
/
;
phi(a) = scaling_cost*phi(a);

* Assignment of parameter values to marginal values
MSE(n) = emf(n)*s(n);
ME(n) $eta(n) = emf(n)/(eta(n));
MC(n,a) $eta(n) = scaling_cost*(  p_f(n,a)/(eta(n))+oc(n) + ME(n)*phi(a));
MSC(n,a) = scaling_cost*(  p_f(n,a)*s(n)+msd(n) + MSE(n)*phi(a) );


Parameter prob(a)       probability of scenario node a in model
/
s0      1
s1      1
s2      0.5
s3      0.5
s4      0.25
s5      0.25
s6      0.25
s7      0.25
s8      0.25
s9      0.25
s10     0.25
s11     0.25
s12     0.25
s13     0.25
s14     0.25
s15     0.25
/
;

$ontext
Parameter prob_2(a) probability for calculation of expected profits;
loop(year,
prob_2(a)$P_Matrix(year,a) = 1 / sum(aa$P_Matrix(year,aa), 1 )
);
;
$offtext

Parameter P0_list(t)  Reference price
/
1       3.337
2       2.844
3       3.357
4       4.549
5       5.207
6       5.395
7       4.980
8       4.561
9       4.984
10      5.412
11      4.692
12      4.066
/
;
Parameter P0(t,a)  Reference price;
P0(t,'s0')=1*scaling_kw*P0_list(t);
P0(t,'s1')=1.025*scaling_kw*P0_list(t);
P0(t,'s2')=1.05*scaling_kw*P0_list(t);
P0(t,'s3')=1.05*scaling_kw*P0_list(t);
P0(t,'s4')=1.075*scaling_kw*P0_list(t);
P0(t,'s5')=1.075*scaling_kw*P0_list(t);
P0(t,'s6')=1.075*scaling_kw*P0_list(t);
P0(t,'s7')=1.075*scaling_kw*P0_list(t);
P0(t,'s8')=1.1*scaling_kw*P0_list(t);
P0(t,'s9')=1.1*scaling_kw*P0_list(t);
P0(t,'s10')=1.1*scaling_kw*P0_list(t);
P0(t,'s11')=1.1*scaling_kw*P0_list(t);
P0(t,'s12')=1.125*scaling_kw*P0_list(t);
P0(t,'s13')=1.125*scaling_kw*P0_list(t);
P0(t,'s14')=1.125*scaling_kw*P0_list(t);
P0(t,'s15')=1.125*scaling_kw*P0_list(t);

sigma(t) = 1.15*1/p0_list(t);

Parameter D0_list(t) Reference demand
/
1       46931
2       46439
3       49381
4       56684
5       60467
6       62074
7       60580
```

```
8       58722
9       59658
10       60721
11       56698
12       50942
/
;

Parameter D0(t,a) reference demand in year a;

D0(t,'s0')=1*scaling_kw*D0_list(t);
D0(t,'s1')=1.025*scaling_kw*D0_list(t);
D0(t,'s2')=1.05*scaling_kw*D0_list(t);
D0(t,'s3')=1.05*scaling_kw*D0_list(t);
D0(t,'s4')=1.075*scaling_kw*D0_list(t);
D0(t,'s5')=1.075*scaling_kw*D0_list(t);
D0(t,'s6')=1.075*scaling_kw*D0_list(t);
D0(t,'s7')=1.075*scaling_kw*D0_list(t);
D0(t,'s8')=1.1*scaling_kw*D0_list(t);
D0(t,'s9')=1.1*scaling_kw*D0_list(t);
D0(t,'s10')=1.1*scaling_kw*D0_list(t);
D0(t,'s11')=1.1*scaling_kw*D0_list(t);
D0(t,'s12')=1.125*scaling_kw*D0_list(t);
D0(t,'s13')=1.125*scaling_kw*D0_list(t);
D0(t,'s14')=1.125*scaling_kw*D0_list(t);
D0(t,'s15')=1.125*scaling_kw*D0_list(t);

Parameter RES_table(t) Feed-in of renewable energy
/
1       14589
2       14508
3       14775
4       16453
5       18842
6       19809
7       18985
8       17002
9       15192
10       14655
11       14717
12       14718
/
;

Parameter RES(t,a) renewables output;
RES(t,'s0')=1*scaling_kw*RES_table(t);
RES(t,'s1')=1.434*scaling_kw*RES_table(t);
RES(t,'s2')=2.033*scaling_kw*RES_table(t);
RES(t,'s3')=2.033*scaling_kw*RES_table(t);
RES(t,'s4')=2.371*scaling_kw*RES_table(t);
RES(t,'s5')=2.371*scaling_kw*RES_table(t);
RES(t,'s6')=2.371*scaling_kw*RES_table(t);
RES(t,'s7')=2.371*scaling_kw*RES_table(t);
RES(t,'s8')=2.865*scaling_kw*RES_table(t);
RES(t,'s9')=2.865*scaling_kw*RES_table(t);
RES(t,'s10')=2.865*scaling_kw*RES_table(t);
RES(t,'s11')=2.865*scaling_kw*RES_table(t);
RES(t,'s12')=3.06*scaling_kw*RES_table(t);
RES(t,'s13')=3.06*scaling_kw*RES_table(t);
RES(t,'s14')=3.06*scaling_kw*RES_table(t);
RES(t,'s15')=3.06*scaling_kw*RES_table(t);

*                              2000    2005    2010    2015    2020    2025    2030    2035
* Germany RES Inst Cap (MW; PRIMES 2012) 22757   48964   77392   110974  157345  183523  221737  236834
* 2010 Index                        x       x       1       1.434   2.033   2.371   2.865   3.06


Parameter alpha(year) Minimum average price expected in each year in cent per kWh
/
2010   4
2015   5
2020   6
2025   7
2030   8
2035   8.5
/
;

Variables
P(t,a)              Price in period t

Positive variables
INVESTMENT(f,n,a)      Investment
q(f,n,t,a)           Production
DIMq(f,n,t,a)          Strictly positive Production
dq(f,n,t,a)           Load gradient
```

```
lambda(f,n,t,a)        Shadow price of startup restriction
kappa(f,n,t,a)         Shadow price of capacity restriction
theta(f,t,a)           Market share
delta(f,n,t,a)         Dual of upper ramp limit
gamma(t,a)             Dual of minimum reserve capacity requirement
omega(year)            Dual of minmimum average price constraint
;

* Fixing ramping variables - there is no ramping constraint in the first period, so no need for a dual variable:
lambda.fx(f,n,t,a)$( ORD(t) = 1 ) = 0 ;
dq.fx(f,n,t,a)$( ORD(t) = 1 ) = 0 ;
delta.fx(f,n,t,a)$( ORD(t) = 1 ) = 0 ;
gamma.fx(t,a)$( ORD(t) = 1 ) = 0 ;

*===============================================================================
* Equations - Stochastic Model
*===============================================================================

Equation profit(f,n,t,a) Stationarity production - perpendicular to q;
profit(f,n,t,a)..
        weeks(a)*discount(a)*prob(a)*MC(n,a) +lambda(f,n,t,a)-lambda(f,n,t+1,a)+kappa(f,n,t,a)+gamma(t,a)
        =g=
        weeks(a)*discount(a)*prob(a)*
        P(t,a)*(1-(theta(f,t,a)/(sigma(t)))$(nash1*nash(f)))
;

Equation profit_inv(f,n,a) Stationarity investment - perpendicular to Investment;
profit_inv(f,n,a)..       # kappas und lambdas hier auf nachfolgejahre/knoten beschränkt. Auch bei Ruud Egging ist das so.   Ausserdem investitionskosten nicht mit *discount(a)*weeks(a)  - INVESTITIONSKOSTEN NICHT MIT PROB MULTIPLIZIEREN?
        investment_cost(n)*discount(a)*prob(a) -sv(n,a)*prob(a)
        =g=
        sum((t),  sum(aa$Ancestor_Matrix(a,aa),  (1/1.09)**(yearnumber(aa)-yearnumber(a)+2.5)*(kappa(f,n,t,aa)  +  gamma(t,a)  +  dq_max(n)*delta(f,n,t,aa))  ) )*available(n)
;

Equation Profit_loadgradient(f,n,t,a) Stationarity load gradient - perpendicular to dq;
Profit_loadgradient(f,n,t,a)$( ORD(t) ge 2 )..        # There is no ramping in the first hour
        weeks(a)*discount(a)*prob(a)*MSC(n,a) - lambda(f,n,t,a) + delta(f,n,t,a)
        =g=
        0
;

Equation market(t,a) Market balance - perpendicular to p;
market(t,a)$(p0(t,a))..
        sum((f,n),q(f,n,t,a))
        =e=
        - RES(t,a) + D0(t,a)* (P(t,a)/(P0(t,a)))**(-sigma(t))
;

Equation market_share(f,t,a) Market share - perpendicular to theta;
market_share(f,t,a)$(nash(f)*nash1)..
        theta(f,t,a)*sum(ff,sum(n,q(ff,n,t,a)$(nash(ff)*nash1)))
        =e=
        sum(n,q(f,n,t,a))
;

Equation capacity_restriction(f,n,t,a) Production capacity restriction - perpendicular to kappa;
capacity_restriction(f,n,t,a)..
        (q_max(f,n,a)+ sum(aa$(Ancestor_Matrix(aa,a)),INVESTMENT(f,n,aa))  )*available(n)
        =g=
        q(f,n,t,a)
;

Equation ramp_restriction(f,n,t,a) Ramping restriction - perpendicular to delta;
ramp_restriction(f,n,t,a)$(ord(t) >= 2)..     # There is no ramp-up constraint in the first hour
        (dq_max(n)*q_max(f,n,a)+ sum(aa$(Ancestor_Matrix(aa,a)),dq_max(n)*INVESTMENT(f,n,aa)))*available(n)
        =g=
        dq(f,n,t,a)
;

Equation load_gradient(f,n,t,a) Load gradient definition- perpendicular to lambda;
load_gradient(f,n,t,a)$( ORD(t) ge 2 )..        # There is no ramp-up constraint in the first hour
        dq(f,n,t,a)
        =g=
        q(f,n,t,a)-q(f,n,t-1,a)
;

Equation reserve_capacity(t,a) Minimum reserve capacity requirement - perpendicular to gamma;
reserve_capacity(t,a)$( ORD(t) ge 2 )..
        sum((f,n), (q_max(f,n,a)+ sum(aa$(ord(a) > ord(aa)),INVESTMENT(f,n,aa)))*available(n) -q(f,n,t,a)) - q_min(a)
        =g=
        0
;

Equation risk_aversion(year) Minimum average price constraint - perpendicular to omega;
risk_aversion(year)..
```

```
        sum(a$(P_Matrix(year,a)),prob(a)*sum(t,P(t,a)/card(t)) )
        =g=
        alpha(year)-omega(year)
;


model   esymmetry2011
/
profit.Q,
profit_inv.INVESTMENT,
profit_loadgradient.DQ,
market.P,
market_share.theta,
capacity_restriction.kappa,
ramp_restriction.delta,
load_gradient.lambda,
reserve_capacity.gamma
*,risk_aversion.omega
/
;

*================================================================================
* Fix values, set starting values, post-calculate parameters
*================================================================================

P.l(t,a)=p0(t,a);
dq.l(f,n,t,a)=0;
P.lo(t,a)=0.0000001;
INVESTMENT.up(f,n,a) = 40000;
*INVESTMENT.up('DE_Dummy',n,a) = 0;
INVESTMENT.up(f,'HC_Retro',a)$(ord(a) ge 2) = q_max(f,'HC_New',a-1)-q_max(f,'HC_New',a);
INVESTMENT.fx(f,'HYD',a) = 0;
INVESTMENT.fx(f,'NUCL',a) = 0;
INVESTMENT.fx(f,'BC_Old',a) = 0;
INVESTMENT.fx(f,'HC_Old',a) = 0;
INVESTMENT.l(f,'NG_CC',a) = 0;
INVESTMENT.l(f,'NG_ST',a) = 0;
INVESTMENT.l(f,'NG_GT',a) = 0;
INVESTMENT.l(f,'O_ST',a) = 0;
q.l(f,n,t,a)=q_max(f,n,a);
q.l(f,'BC_Old',t,a)=q_max(f,'BC_Old',a)*available('BC_Old');
q.l(f,'HC_Old',t,a)=q_max(f,'HC_Old',a)*available('HC_Old');
q.l(f,'HC_New',t,a)= q_max(f,'HC_New',a)*available('HC_New') ;
q.l(f,'HYD',t,a)=q_max(f,'HYD',a)*available('HYD');
q.l(f,'NUCL',t,a)=q_max(f,'NUCL',a)*available('NUCL');
q.l(f,'NG_ST',t,a)= 0 ;
q.l(f,'NG_GT',t,a)= 0 ;
q.l(f,'NG_CC',t,a)= 0 ;
q.l(f,'CC_New',t,a)= q_max(f,'CC_New',a)*available('CC_New') ;
q.l(f,'NG_GT_New',t,a)= q_max(f,'NG_GT_New',a)*available('NG_GT_New') ;
q.l(f,'O_ST',t,a)= 0 ;
q.l(f,'O_GT',t,a)= 0 ;


$ontext
*================================================================================
* Fix starting values to previous runs
*================================================================================

Parameter
q_starting_value(f,n,t,a)
dq_starting_value(f,n,t,a)
INVESTMENT_starting_value(f,n,a)
p_starting_value(t,a)
;

*$libinclude xlimport q_starting_value          .\output-stochastic.xls q!b3:s7803
*$libinclude xlimport dq_starting_value         .\output-stochastic.xls dq!b3:s7803
*$libinclude xlimport INVESTMENT_starting_value .\output-stochastic.xls INVESTMENT!b3:r68
*$libinclude xlimport p_starting_value          .\output-stochastic.xls price!b3:q123

Q.l(f,n,t,a)=q_starting_value(f,n,t,a);
DQ.l(f,n,t,a)=dq_starting_value(f,n,t,a);
INVESTMENT.l(f,n,a)=INVESTMENT_starting_value(f,n,a);
P.l(t,a)=p_starting_value(t,a);
$offtext

* Tell GAMS that Investment in last model year must be zero. Otherwise empty equation profit_inv without dual fixed.
INVESTMENT.fx(f,n,'s12')=0;
INVESTMENT.fx(f,n,'s13')=0;
INVESTMENT.fx(f,n,'s14')=0;
INVESTMENT.fx(f,n,'s15')=0;


*================================================================================
* Fix investment levels for calculation of Value of Stochastic Solution
```

```
*==========================================================================================

*Parameter
*INVESTMENT_deterministic(f,n,a);
*$libinclude xlimport INVESTMENT_deterministic .\output-deterministic.xls INVESTMENT-for-VSS-Calculation!b3:s68
*INVESTMENT.fx(f,n,a)=INVESTMENT_deterministic(f,n,a);

*==========================================================================================
* Solve statement
*==========================================================================================

solve esymmetry2011 using mcp;

*==========================================================================================
* Excel Output
*==========================================================================================


TC(f,a)= sum((n,t), q.l(f,n,t,a)*MC(n,a)+dq.l(f,n,t,a)*MSC(n,a))*weeks(a) + sum(n, investment_cost(n)*INVESTMENT.l(f,n,a));
TRev(f,a)= sum(t,P.l(t,a)*sum(n,q.l(f,n,t,a)))*weeks(a);
TP(f,a)= TRev(f,a)-TC(f,a);
Expected_profits(f)=sum(a, TP(f,a)*prob(a)*discount(a));
e(a) = sum(f,sum(n,sum(t,q.l(f,n,t,a)*emf(n)/(eta(n)+0.001)+ s(n)*emf(n)*dq.l(f,n,t,a))));
TQ_tech(t,a,n)=sum(f, Q.l(f,n,t,a));
TQ_tech_s1(t,n)=sum(f, Q.l(f,n,t,'s1'));
TQ(t,a)=sum((f,n), Q.l(f,n,t,a));
FullLoadHour(n,a)= sum((f,t), Q.l(f,n,t,a))/( (sum(f, q_max(f,n,a)+ 0.0001 + sum(aa$(ord(a) > ord(aa)),INVESTMENT.l(f,n,aa)))) *card(t)) *8760;
AveragePrice(a)=sum(t,P.l(t,a))/card(t);
Renewable_share(a)=sum(t,RES(t,a)+sum(f,Q.l(f,'HYD',t,a)))/sum(t,sum((f,n),Q.l(f,n,t,a))+0.0001+RES(t,a));
Yearly_demand(a)=sum(t,sum((f,n),Q.l(f,n,t,a))+RES(t,a))*8760/card(t)*1/1000000;

display Q.l, DQ.L, TQ, TQ_tech_s1, RES, P.l, mc, msc, FullLoadHour, AveragePrice, Renewable_share, Yearly_demand, INVESTMENT.l, Expected_profits,TP,
TC, TRev;


*** Write zeros in EXCEL file
TQ(t,a)$(not TQ(t,a)) = eps;
P.l(t,a)$(not P.l(t,a)) = eps;
q_max(f,n,a)$(not q_max(f,n,a)) = eps;
INVESTMENT.l(f,n,a)$(not INVESTMENT.l(f,n,a)) = eps;
TQ_tech_s1(t,n)$(not TQ_tech_s1(t,n)) = eps;
lambda.l(f,n,t,a)$(not lambda.l(f,n,t,a)) = eps;
delta.l(f,n,t,a)$(not delta.l(f,n,t,a)) = eps;
kappa.l(f,n,t,a)$(not kappa.l(f,n,t,a)) = eps;
q.l(f,n,t,a)$(not q.l(f,n,t,a)) = eps;
dq.l(f,n,t,a)$(not dq.l(f,n,t,a)) = eps;

*** Write output in EXCEL file
$libinclude xldump P.l output-stochastic.xls price!b3
$libinclude xldump TQ_tech_s1 output-stochastic.xls production!b3
$libinclude xldump INVESTMENT.l output-stochastic.xls INVESTMENT!b3
$libinclude xldump Expected_profits output-stochastic.xls PROFITS!b3
```

GAMS Code of the model in Chapter 5

```
*==========================================================================================
* Andreas Schroeder November 2012
* Model EMELIE-ESY as contribution to EMF 28
* Scenario EU1/ 40%DEF  of EMF28
* Model run requires access to the file "Input_Esy_2050-2012-08-28.xls" and to the file "Set-E-2.dat" and the file "NTC-2012-08-31.xls"
*==========================================================================================

option mcp = path;
option iterlim = 10000000;
option reslim = 30000;
$batinclude Set-E-2.dat
set
f          Firm
t          Time step      /1*24/
y          Period         /2010,2020,2030,2040,2050/
n          Technology   /BC_old, HC_old, BC_SCP, HC_SCP, G_CC, G_GT, NUC_NEW, BC_CCS, HC_IGCCCCS, O_ST, O_GT, G_ST, NUC_old, G_CCS,
HYD /
r          Region
link(r,r)      Interregional exchange possibility
local(f,r)     Assigns regions to firms
nash(f)               Firmen die sich nach Nash verhalten;
nash(f):=no;
scalar       nash1               Nash-Verhalten von Firmen          /0/ ;
alias (f,ff),(r,rr),(n,nn),(y,yy);
```

```
link(r,rr) = yes;
link(r,r) = no;

parameter
g(y)          Year indication /2010 2010, 2020 2020, 2030 2030, 2040 2040, 2050 2050/
exlim(y,r,rr)   Installed export capacity
q_max(y,f,n)    Installed capacity of firm f and technology n
i_max(y,f,n)    Planned construction of firm f and technology n
D0(r,t)        Reference demand in region r and period t
P0(r,t)        Reference price in region r and period t
psi(r)         Ten year demand growth rate
*energy efficiency ref
/Germany        0.1, Austria        0.1, Switzerland     0.1, France        0.1, Italy        0.1, Poland        0.2, Netherlands     0.1, Belgium        0.1, Czech
0.2, Norway        0.1, BALTIC        0.2, BRIT        0.1, SEAST        0.2, IBERIA        0.1, NORDIC        0.1/
*energy efficiency high
*/Germany        0.05, Austria        0.05, Switzerland     0.05, France        0.1, Italy        0.05, Poland        0.1, Netherlands     0.1, Belgium        0.1,
Czech        0.1, Norway        0.05, BALTIC        0.1, BRIT        0.05, SEAST        0.1, IBERIA        0.05, NORDIC        0.05/
s(n)          Ramp up fuel requirement
dq_max(n)       Maximum load gradient
p_f(y,n)       Fuel cost of tech n  in cent pro kwh
emf(n)         Emissions factor
eta(n)         Degree of efficiency of tech n
oc(n)          Operating cost of tech n in t
a(n)           Availability of technology n
epsilon0        Demand elasticity /0.3/
RES(y,r,t)      Inelastic supply of RES
delta          Private discount rate /0.08/
MC(y,n)         Marginal Costs
ME(n)          Marginal Emissions
MSD(n)          Marginal ramp up depreciation
MSC(y,n)        Marginal ramp up costs
MSE(n)          Marginal ramp up emissions
FC(y,n)         Fix costs of investment in technology n in cent per kW
rep           Factor to transform represented production period into investment horizon
hcs(n,f,t)      Firm specific regional availability hydro correction factor
cap(y)         Emission cap in period y
*mitigation 1 scenario
*/2010 1.265, 2020 0.956, 2030 0.647, 2040 0.338, 2050  0.029/
*reference scenario
/2010 1.265, 2020 1.0576, 2030 0.8502, 2040 0.6427, 2050  0.4353/
resf(y)        Renewables up scaling
* reference RES
/2010 0, 2020 0, 2030 0, 2040 0, 2050 0/
* high RES
*/2010 0, 2020 0, 2030  0.1, 2040 0.2, 2050 0.3/
;

$libinclude xlimport FC        .\Input_Esy_2050-2012-08-28.xls    a2:p7
$libinclude xlimport p_f       .\Input_Esy_2050-2012-08-28.xls    a10:p15
$libinclude xlimport eta       .\Input_Esy_2050-2012-08-28.xls    a20:o21
$libinclude xlimport oc        .\Input_Esy_2050-2012-08-28.xls    a24:o25
$libinclude xlimport s         .\Input_Esy_2050-2012-08-28.xls    a28:o29
$libinclude xlimport dq_max     .\Input_Esy_2050-2012-08-28.xls    a32:o33
$libinclude xlimport emf       .\Input_Esy_2050-2012-08-28.xls    a36:o37
$libinclude xlimport MSD       .\Input_Esy_2050-2012-08-28.xls    a40:o41
$libinclude xlimport a         .\Input_Esy_2050-2012-08-28.xls    a44:o45
$libinclude xlimport D0        .\Input_Esy_2050-2012-08-28.xls    a50:y65
$libinclude xlimport P0        .\Input_Esy_2050-2012-08-28.xls    a70:y85
$libinclude xlimport RES       .\Input_Esy_2050-2012-08-28.xls    a90:z165
$libinclude xlimport q_max      .\Input_Esy_2050-2012-08-28.xls    a180:k255
$libinclude xlimport i_max      .\Input_Esy_2050-2012-08-28.xls    r180:y255
;


display q_max, D0, P0, RES;

resf(y)=0;
MC(y,n)=p_f(y,n)/eta(n)+oc(n);
ME(n)=emf(n)/eta(n);
rep =(sum(y$(ord(y)=2),g(y))-sum(y$(ord(y)=1),g(y))) *8760/card(t);
MSC(y,n)= p_f(y,n)*s(n)+MSD(n);
MSE(n)=emf(n)*s(n);


parameter slope(r,t,y)       Slope of demand function;
slope(r,t,y)$D0(r,t) = P0(r,t)/(-epsilon0*D0(r,t)*(1+psi(r))**(ord(y)-1))
;

parameter intercept(r,t,y)    Intercept of demand function;
intercept(r,t,y)$D0(r,t) = P0(r,t)-D0(r,t)*(1+psi(r))**(ord(y)-1)*slope(r,t,y)
;

display intercept, slope;

*******************************************************************************
***     Export limits (NTCs)
```

```
********************************************************************************

Parameter NTC_2010(r,rr);
Parameter NTC_2040(r,rr);
Parameter NTC_2020(r,rr);
Parameter NTC_2030(r,rr);
Parameter NTC_2050(r,rr);

$libinclude xlimport NTC_2010    .\NTC-2012-08-31.xls    a4:p19
$libinclude xlimport NTC_2020    .\NTC-2012-08-31.xls    a23:p38
$libinclude xlimport NTC_2030    .\NTC-2012-08-31.xls    a42:p57
$libinclude xlimport NTC_2040    .\NTC-2012-08-31.xls    a61:p76
$libinclude xlimport NTC_2050    .\NTC-2012-08-31.xls    a80:p95

display NTC_2010;
display NTC_2020;
display NTC_2030;
display NTC_2040;
display NTC_2050;

exlim('2010',r,rr)=NTC_2010(r,rr);
exlim('2020',r,rr)=NTC_2020(r,rr);
exlim('2030',r,rr)=NTC_2030(r,rr);
exlim('2040',r,rr)=NTC_2040(r,rr);
exlim('2050',r,rr)=NTC_2050(r,rr);

********************************************************************************
***      Variables
********************************************************************************
Variable
P(r,t,y)              Price in region r and period t in Period y
;

positive
variables
Po(y,r,t)             Ordered prices for output
i(f,n,y)              Investment of firm f in technology n in period y
q(y,f,n,t)            Production of firm f in technology n in step t and Period y
theta(y,f,t,r)        Market share dual
x(r,rr,t,y)           Export of region r to region rr in step t and Period y
e(y,f)                Annual Emissions from sectoral production in period y in tons
phi(y)                Carbon Dioxide emissions price
DIMi(r,y)             Imports of region r in Period y
DIMx(rr,y)            Export of region r in Period y
dq(y,f,n,t)           Load gradient of firm f in technology n in step t and Period y
lambda(y,f,n,t)       Shadow price of load-gradient restriction of firm f in technology n in step t and Period y
kappa(y,f,n,t)        Shadow price of capacity restriction of firm f in technology n in step t and Period y
rho(y,f,n,t)          Shadow price of ramping requirement
tau(r,rr,t,y)         Shadow price of transmission r to rr in step t and Period y
iota(f,n,y)           Shadow price of investment restriction
;

* WARUM IST EXPORT IMMER POSITIV? KEIN IMPORT?

equations
profit_i(f,n,y)
profit_q(y,f,n,t)
profit_dq(y,f,n,t)
profit_x(r,rr,t,y)
trans(r,rr,t,y)
market(r,t,y)
market_share(y,f,t,r)
emission(y,f)
emission_market(y)
capacity_restriction(y,f,n,t)
load_gradient_restriction(y,f,n,t)
ramp_requirement(y,f,n,t)
investment_constraint(f,n,y)
;

********************************************************************************
***      Equations
********************************************************************************


profit_q(y,f,n,t)..
MC(y,n)+phi(y)*ME(n)
+kappa(y,f,n,t)
- sum(r$local(f,r),P(r,t,y))
+((1/epsilon0)*sum(r$local(f,r),(P0(r,t)/(D0(r,t)*(1+psi(r))**(ord(y)-1))))*sum(nn,q(y,f,nn,t)))$(nash1*nash(f))
+rho(y,f,n,t)$(ord(t)>1)-rho(y,f,n,t+1)
=g= 0
;

market_share(y,f,t,r)$(local(f,r)*nash(f)*nash1)..
theta(y,f,t,r)*(D0(r,t)*(1+psi(r))**(ord(y)-1))=e=sum(n,q(y,f,n,t))
```

```
;

market(r,t,y)..
sum(n,sum(f$local(f,r),q(y,f,n,t)))+sum(rr$link(r,rr),x(rr,r,t,y)-x(r,rr,t,y))
+ (1+resf(y))*RES(y,r,t)
- (D0(r,t)*(1+psi(r))**(ord(y)-1))-((D0(r,t)*(1+psi(r))**(ord(y)-1))/P0(r,t))*(P0(r,t)-P(r,t,y))*(1/epsilon0)**(-1)
=e=0
;

profit_i(f,n,y)..
(FC(y,n)+iota(f,n,y))- (rep*(sum(yy$(ord(yy)>=ord(y)),sum(t,(kappa(yy,f,n,t)+lambda(yy,f,n,t)*dq_max(n)) *a(n)*(1/(1+delta))**(g(yy)-g(y)+4)))))
=g=0
*letzter Term für Diskontierung mit dem 4. Jahr einer Periode als Referenzjahr für die Berechnung der Diskontierung
;

profit_dq(y,f,n,t)$( ORD(t) > 1 )..
MSC(y,n)+MSE(n)*phi(y)+lambda(y,f,n,t)-rho(y,f,n,t)  =g=0
;

investment_constraint(f,n,y)..
i_max(y,f,n)
-i(f,n,y)=g= 0
;

profit_x(r,rr,t,y)..
P(r,t,y)=g= P(rr,t,y)-tau(r,rr,t,y)
;

trans(r,rr,t,y)..
exlim(y,r,rr)- x(r,rr,t,y)=g= 0
;

emission_market(y)..
cap(y)-sum(f,e(y,f))=g=0
;

emission(y,f)..
e(y,f)=e=sum(t,  sum(n, q(y,f,n,t)*ME(n)+ dq(y,f,n,t)*MSE(n))) *(rep/10)*1/1000000000
;

capacity_restriction(y,f,n,t)..
(q_max(y,f,n)+sum(yy$(ord(yy)<=ord(y)),i(f,n,yy)))*a(n)  -  q(y,f,n,t)
=g= 0
;

load_gradient_restriction(y,f,n,t)$( ORD(t) > 1 )..
dq_max(n)*(q_max(y,f,n)+sum(yy$(ord(yy)<=ord(y)),i(f,n,yy)))*a(n)-(q(y,f,n,t)-q(y,f,n,t-1)$(ord(t)>1)  )=g= 0
;

ramp_requirement(y,f,n,t)$( ORD(t) > 1 )..
dq(y,f,n,t)-(q(y,f,n,t)-q(y,f,n,t-1)$(ord(t)>1))=g= 0
;

lambda.fx(y,f,n,t)$( ORD(t) = 1 ) = 0
;

rho.fx(y,f,n,t)$( ORD(t) = 1 ) = 0
;

dq.fx(y,f,n,t)$( ORD(t) = 1 ) = 0
;



model   EMELIE_Esy_2050
/
profit_q.q,
profit_dq.dq,
profit_i.i,
profit_x.x,
trans.tau,
market.p,
market_share.theta,
emission.e,
emission_market.phi,
investment_constraint.iota,
capacity_restriction.kappa,
load_gradient_restriction.lambda,
ramp_requirement.rho
/
;

*******************************************************************************
***      Set starting values
*******************************************************************************
```

```
P.l(r,t,y)=5;
phi.l(y)=1;
i.l(f,n,y)=0;
q.l(y,f,n,t)=q_max(y,f,n)*a(n);

* Fix first-period investment
i.fx(f,n,'2010')=0;

* Set minimum price to avoid infeasibility under iso-elastic demand function
*P.lo(r,t,y)= 0.000001;


********************************************************************************
***      Solve and report
********************************************************************************


solve EMELIE_Esy_2050 using mcp;

Po.l(y,r,t):= P.l(r,t,y);
DIMx.l(r,y):=sum(t,sum(rr,x.l(r,rr,t,y)))+0.000000001;
DIMi.l(r,y):=sum(t,sum(rr,x.l(rr,r,t,y)))+0.000000001;
P.l(r,t,y)$(not P.l(r,t,y)) = eps;
i.l(f,n,y)$(not i.l(f,n,y)) = eps;
q.l(y,f,n,t)$(not q.l(y,f,n,t)) = eps;
x.l(r,rr,t,y)$(not x.l(r,rr,t,y)) = eps;
e.l(y,f) $(not e.l(y,f )) = eps;
phi.l(y) $(not phi.l(y)) = eps;

Parameter
qtot(y,f,n)               Production of firm f in Period y;
qtot(y,f,n):=sum(t,q.l(y,f,n,t))*360/1000000;


Parameter
PRODUCTION(f,y)          Production in TWh per Year
P_EMF(r,y)               Price in 2010 EUR per GJ
I_EMF(n,f,y)             Capacity Investment in GW
Q_FOSSILS(n,f,y)         Production in EJ per year
EXPORT_EMF(r,y)          Trade Export in EJ per year
IMPORT_EMF(r,y)          Trade Import in EJ per year
EMISSIONPRICE(y)         Emission price in EUR per t CO2
EMISSIONS(f,y)           Emissions in Mt CO2 per year
CUM_CAPACITY(n,f,y)      Cumulative Capacity in GW per year
EFFICIENCY(n)            Efficiency in percent
FULL_LOAD_HOURS(f,n,y)   Yearly full load hours
AVERAGE_PRICE(r,y)       Yearly average price in EUR per MWh
Annuity(n)               Annuity for capital cost
LCoE(f,n,y)              Levelized cost of electricity in EUR per MWh
INVESTMENT(f,y)          Investment in billion EUR per year
lifetime(n)              Lifetime of power plants in years
/BC_old 50, HC_old 50, BC_SCP 50, HC_SCP 50, G_CC 40, G_GT 35, O_ST 50, O_GT 35, G_ST 50, NUC_old 50, NUC_New 50, BC_CCS 50, HC_IGCCCCS
50, G_CCS 40, HYD 100/
;


PRODUCTION(f,y)=sum((t,n), Q.l(y,f,n,t)+(1+resf(y))*sum(r$local(f,r),RES(y,r,t)))*8760/card(t)*1/1000000;
P_EMF(r,y)=sum(t, P.l(r,t,y))/card(t)*10;
I_EMF(n,f,y)=i.l(f,n,y)/1000;
Q_FOSSILS(n,f,y)=sum(t, Q.l(y,f,n,t))*0.0000000036*8760/card(t);
EXPORT_EMF(r,y)=sum((rr,t),X.l(r,rr,t,y))*0.0000000036*8760/card(t);
IMPORT_EMF(r,y)=sum((rr,t),X.l(rr,r,t,y))*0.0000000036*8760/card(t);
EMISSIONPRICE(y)=phi.l(y)*10;
EMISSIONS(f,y)=e.l(y,f)*1000;
CUM_CAPACITY(n,f,y)=(q_max(y,f,n)+sum(yy$(ord(yy)<=ord(y)),i.l(f,n,yy)))/1000;
EFFICIENCY(n)=eta(n);
FULL_LOAD_HOURS(f,n,y)=sum(t,q.l(y,f,n,t))/((q_max(y,f,n)+sum(yy$(ord(yy)<=ord(y)),i.l(f,n,yy))+0.0001)*card(t))*8760;
ANNUITY(n)=(1+delta)**lifetime(n)*delta/((1+delta)**lifetime(n)-1);
LCOE(f,n,y)=ANNUITY(n)*FC(y,n)*10/(FULL_LOAD_HOURS(f,n,y)+0.000001)+MC(y,n)*10+phi.l(y)*ME(n)*10;
INVESTMENT(f,y)=sum(n,i.l(f,n,y)*1000*FC(y,n)/1000000000000);

I_EMF(n,f,y)$(not I_EMF(n,f,y)) = eps;
Q_FOSSILS(n,f,y)$(not Q_FOSSILS(n,f,y)) = eps;
EXPORT_EMF(r,y)$(not EXPORT_EMF(r,y)) = eps;
IMPORT_EMF(r,y)$(not IMPORT_EMF(r,y)) = eps;
CUM_CAPACITY(n,f,y)$(not CUM_CAPACITY(n,f,y)) = eps;
EFFICIENCY(n)$(not EFFICIENCY(n)) = eps;
INVESTMENT(f,y)$(not INVESTMENT(f,y))=eps;

display MSC, MC, ME, MSE, P_EMF, I_EMF, Q_FOSSILS, EXPORT_EMF, IMPORT_EMF, EMISSIONS,
EMISSIONPRICE, CUM_CAPACITY, EFFICIENCY, FULL_LOAD_HOURS, ANNUITY, LCOE, INVESTMENT, PRODUCTION;

$libinclude xldump P_EMF              .\EMF_EU1.xls Price
$libinclude xldump I_EMF              .\EMF_EU1.xls New_Capacity
$libinclude xldump Q_FOSSILS          .\EMF_EU1.xls Production
```

```
$libinclude xldump EXPORT_EMF          .\EMF_EU1.xls Export
$libinclude xldump IMPORT_EMF          .\EMF_EU1.xls Import
$libinclude xldump EMISSIONS           .\EMF_EU1.xls Emissions
$libinclude xldump EMISSIONPRICE       .\EMF_EU1.xls CO2price
$libinclude xldump CUM_CAPACITY        .\EMF_EU1.xls Cum_Capacity
$libinclude xldump EFFICIENCY          .\EMF_EU1.xls Efficiency
$libinclude xldump LCoE                .\EMF_EU1.xls LCOE
$libinclude xldump INVESTMENT          .\EMF_EU1.xls Investment
$libinclude xldump FULL_LOAD_HOURS     .\EMF_EU1.xls FullLoadHours
;
```

GAMS Code of the model in Chapter 6

```
*===================================================================================
* Andreas Schröder – May 2012
* Projektstudium 2011 – Model on grid congestion in Germany and the effects of HVDC lines and the strategic placement of generation resources
* Model run requires access to the file “input.xls”
*===================================================================================

sets
n             Node or Zone      /PT,ES,FR,NL,BE,LX,DK-W,CH,AU,IT,PL,CZ,SK,HU,SN,CR,UA,21,22,23,24,25,26,41,42,71,72,73,74,75,76,81,82,83,84,SE,DK-
E,NO,GB/
Ger(n)        Nodes in Germany  /21,22,23,24,25,26,41,42,71,72,73,74,75,76,81,82,83,84/
dcl           DC Line           /dc1*dc12,dc18*dc34,dc36*dc50,dc51*dc53/
t             Time              /t1*t1008/
st            Storage           /pump,battery,acaes/
s             Type of plant
/
Lignite
Coal
Gas
Oil
Nuclear
Biomass
/
Flexible(s)           Subset of flexible plants /Gas,Oil/
Fossil(s)             Subset of fossil-fired plants /Coal,Gas,Nuclear/
CHP_technologies(s)   Subset of CHP-able technology plants /Coal,Gas,Nuclear,Biomass/
l                     Ordinary AC Line /Line2*line3643/
;

Alias    (t,tt),(n,nn);

option reslim = 120000000;
option iterlim = 100000000;
option
   limrow = 0,
   limcol = 0,
   solprint = off,
   sysout = off;
option savepoint=1 ;

$onecho > cplex.opt
threads 4
$offecho


*------------------------------------------------------------------------------*
* Some parameters
*------------------------------------------------------------------------------*

scalars
epsilon       Demand elasticity at reference point      / -0.2/
loadfactor    Factor to define load levels              / 1.0 /
windfactor    Factor to define wind generation          / 1.0 /
pvfactor      Factor to define pv generation            / 1.0 /
trm           Transmission reliability margin           / 0.2 /
c_dsm_l       DSM costs low                             / 3   /
c_dsm_m       DSM costs medium                          / 5   /
c_dsm_h       DSM costs high                            / 10  /
;

parameter revision(s)    Factor defining the availabilty of plant types
/
Lignite  0.9
Coal     0.9
Gas      0.95
Oil      0.95
Nuclear  0.9
Biomass  0.95
/
;
```

```
display revision;

*------------------------------------------------------------------------------*
* Line parameters
*------------------------------------------------------------------------------*
parameter
        AC_P_max(l)      Maximum Capacity of line dcl
        PTDF(l,n)        Power Transfer Distribution Factor
;

$call GDXXRW "input.xls" par=AC_P_max rng=AC_Capacity!A2:b263 cdim=0 rdim=1
$gdxin input.gdx
$load AC_P_max
;

$call GDXXRW "input.xls" par=PTDF rng=PTDF!A1:AN263 cdim=1 rdim=1
$gdxin input.gdx
$load PTDF
;

Parameter AC_Incidence(l,n);
$call GDXXRW "input.xls" par=AC_Incidence rng=AC_Capacity!m1:AZ263 cdim=1 rdim=1
$gdxin input.gdx
$load AC_Incidence
;

AC_P_max(l) = (1-trm) * AC_P_max(l);

display AC_P_max, PTDF;

Parameter DC_P_max(dcl)    Maximum Capacity of line dcl;
*NEP DC
*$call GDXXRW "input.xls" par=DC_P_max rng=DC_Capacity!A2:b45 cdim=0 rdim=1
*OHNE DC
*$call GDXXRW "input.xls" par=DC_P_max rng=DC_Capacity!A2:b30 cdim=0 rdim=1
*Selektierte HGÜ
$call GDXXRW "input.xls" par=DC_P_max rng=DC_Capacity!A2:b32 cdim=0 rdim=1
$gdxin input.gdx
$load DC_P_max
;

Parameter DC_Incidence(dcl,n);
*NEP DC
*$call GDXXRW "input.xls" par=DC_Incidence rng=DC_Incidence!A1:AN45 cdim=1 rdim=1
*OHNE DC
*$call GDXXRW "input.xls" par=DC_Incidence rng=DC_Incidence!A1:AN30 cdim=1 rdim=1
*Selectierte HGÜ
$call GDXXRW "input.xls" par=DC_Incidence rng=DC_Incidence!A1:AN32 cdim=1 rdim=1
$gdxin input.gdx
$load DC_Incidence
;

display DC_Incidence, DC_P_max;


*------------------------------------------------------------------------------*
* Generation capacities
*------------------------------------------------------------------------------*

Parameter g_max(s,n) Generation capacities of current fossil plants;
$call GDXXRW "input.xls" par=g_max rng=g_max!A2:Ao8 cdim=1 rdim=1
$gdxin input.gdx
$load g_max
;

display g_max;

Parameter Wind_max(t,n) Wind generation;
$call GDXXRW "input.xls" par=Wind_max rng=Wind!A2:AN1010 cdim=1 rdim=1
$gdxin input.gdx
$load Wind_max

Parameter PV_max(t,n) PV generation;
$call GDXXRW "input.xls" par=PV_max rng=PV!A2:AN1010 cdim=1 rdim=1
$gdxin input.gdx
$load PV_max

Parameter Hydro_max(t,n) Hydro-electric generation;
$call GDXXRW "input.xls" par=Hydro_max rng=Hydro!A2:AN1010 cdim=1 rdim=1
$gdxin input.gdx
$load Hydro_max


*------------------------------------------------------------------------------*
```

```
* Reference demand  (linear demand fucntion p = a + m*q )
*------------------------------------------------------------------------------*


parameter q_ref(t,n) Average demand;
$call GDXXRW "input.xls" par=q_ref rng=demand!A2:AN1010 cdim=1 rdim=1
$gdxin input.gdx
$load q_ref
;

display q_ref;

Parameter  p_ref(t)      Reference price for demand function;
$call GDXXRW "input.xls" par=p_ref rng=Price!A3:B1010 cdim=0 rdim=1
$gdxin input.gdx
$load p_ref
;

display p_ref;

parameter m(t,n)         Slope of demand function;
m(t,n)$q_ref(t,n) = p_ref(t)/(epsilon*loadfactor*q_ref(t,n))
;

parameter a(t,n)         Intercept of demand function;
a(t,n)$q_ref(t,n) = p_ref(t)-loadfactor*q_ref(t,n)*m(t,n)
;

display m,a;


*------------------------------------------------------------------------------*
* Generation costs
*------------------------------------------------------------------------------*

Parameter c(s)         Erzeugungskosten der Kraftwerkstypen in EUR per MW including carbon cost
/
Lignite  25
Coal     35
Gas      55
Oil      95
Nuclear  25
Biomass  70
/
;


Parameter ramp_percentage(s)
/
Lignite  0.5
Coal     0.5
Gas      1
Oil      1
Nuclear  0.33
Biomass  1
/
;

Parameter ramp_cost(s)    marginal ramping cost
/
Lignite  25
Coal     35
Gas      55
Oil      95
Nuclear  25
Biomass  70
/
;

Parameter ramp_limit(s,n);
ramp_limit(s,n)=ramp_percentage(s)*g_max(s,n);



*------------------------------------------------------------------------------*
* Storage parameters
*------------------------------------------------------------------------------*


Parameter S_eff(st) Conversion efficiency storage
/
pump     0.75
battery  0.8
acaes    0.7
/
;
```

```
Parameter Scap_max(st,n) Storage capacity limit;
$call GDXXRW "input.xls" par=Scap_max rng=storage_cap!A1:an4 cdim=1 rdim=1
$gdxin input.gdx
$load Scap_max
;

Parameter Sin_max(st,n) Storage capacity limit;
$call GDXXRW "input.xls" par=Sin_max rng=storage_inflow!A1:an4 cdim=1 rdim=1
$gdxin input.gdx
$load Sin_max
;

Parameter Sout_max(st,n) Storage outflow power limit;
Sout_max(st,n) = Sin_max(st,n)
;

display S_eff, Sin_max, Scap_max, Sout_max;

*AUSSCHALTEN
*Sin_max('battery',n) = 0;
*Sin_max('acaes',n) = 0;
*Sout_max('battery',n)=0;
*Sout_max('acaes',n)=0;



*------------------------------------------------------------------------------*
* Demand-Side-Management parameters
*------------------------------------------------------------------------------*


Parameter dsm_max_l(t,n) Limit;
dsm_max_l(t,n)=0.02*q_ref(t,n);

Parameter dsm_max_m(t,n) Limit;
dsm_max_m(t,n)=0.02*q_ref(t,n);

Parameter dsm_max_h(t,n) Limit;
dsm_max_h(t,n)=0.01*q_ref(t,n);

display dsm_max_l, dsm_max_m, dsm_max_h;

*AUSSCHALTEN
*dsm_max_l(t,n)=0;
*dsm_max_m(t,n)=0;
*dsm_max_h(t,n)=0;


*------------------------------------------------------------------------------*
* Variables and equations
*------------------------------------------------------------------------------*

Variables
w                       Welfare
q_area(t)               Area under demand function
variablecost(t)         Total cost
AC_lineflow(l,t)        Lineflow on l
AC_netinput(t,n)        Net input at node n
DC_lineflow(dcl,t)      Lineflow on dcl
DC_netinput(t,n)        Net input at node n
;

Positive Variables
q(t,n)                  Demand at node n
g(t,s,n)                Generation of plant type s of firm f at node n
SIN(st,n,t)             Storage inflow
SOUT(st,n,t)            Storage outflow
g_up(t,s,n)             Generation change from one period to the next
S_LEVEL(st,n,t)         Storage level
DSM_out_l(n,t)          DSM shifting load
DSM_in_l(n,t)           DSM adding load
DSM_out_m(n,t)          DSM shifting load
DSM_in_m(n,t)           DSM adding load
DSM_out_h(n,t)          DSM shifting load
DSM_in_h(n,t)           DSM adding load
;

Equations
objective                       Zielfunktion der Maximierung (Wohlfahrtsfunktion)
nodal_balance(t,n)              Nebenbedingung1: Erzeugung = Nachfrage + NetInput
gen_constraint(t,s,n)           Nebenbedingung3: kein Kraftwerk darf mehr Erzeugen als es kann
ramp_limit_constraint(t,s,n)    Ramping limits for power plants
ramp_up_constraint(t,s,n)       Ramping up constraint for power plants

AC_Constraint_LineFlow(l,t)     power flow for each line [MW]
```

```
AC_Constraint_LineFlow_pos(l,t)        transmission limit positive [MW]
AC_Constraint_LineFlow_neg(l,t)        transmission limit negative [MW]
AC_NetInput_Constraint(t)              Net inputs have to sum to zero over all nodes
*DC_NetInput_Constraint(t)             Net inputs have to sum to zero over all nodes
DC_Constraint_LineFlow(n,t)            power flow for each line [MW]
DC_Constraint_LineFlow_pos(dcl,t)      transmission limit positive [MW]
DC_Constraint_LineFlow_neg(dcl,t)      transmission limit negative [MW]

Spowerlimit_in1(st,t,n)                Power limit storage inflow
Spowerlimit_out1(st,t,n)               Power limit storage outflow
Storage_level(st,t,n)                  Storage level at time t and node n
Slimit_upper1(st,t,n)                  Capacity limit storage outflow (kann nicht mehr rein als capacity limit)
Storage_Balance(st,n,t)                Storage Balance

DSMlimit_upper_l(t,n)                  Maximum of (positive) demand-side management
DSMlimit_lower_l(t,n)                  Maximum of (negative) demand-side management
DSMlimit_upper_m(t,n)                  Maximum of (positive) demand-side management
DSMlimit_lower_m(t,n)                  Maximum of (negative) demand-side management
DSMlimit_upper_h(t,n)                  Maximum of (positive) demand-side management
DSMlimit_lower_h(t,n)                  Maximum of (negative) demand-side management
DSMbalance_l(t,n)                      Demand-side management balance restricts the period within which load can be shifted
DSMbalance_m(t,n)                      Demand-side management balance restricts the period within which load can be shifted
DSMbalance_h(t,n)                      Demand-side management balance restricts the period within which load can be shifted
CHP_constraint_lignite                 CHP condition for lignite
CHP_constraint_coal                    CHP condition for coal
CHP_constraint_biomass                 CHP condition for biomass
CHP_constraint_gas_oil                 CHP condition for gas and oil
;

objective..                   w =e= ( sum(t, sum (n, (a(t,n)*q(t,n)+0.5*m(t,n)*sqr(q(t,n))))  - sum((s,n), g(t,s,n)*c(s))
                           - sum(n, c_dsm_l*DSM_out_l(n,t))-sum(n,c_dsm_m*DSM_out_m(n,t))-sum(n,c_dsm_h*DSM_out_h(n,t))
                           - sum((s,n),g_up(t,s,n)*ramp_cost(s))) ) / 1
;
nodal_balance(t,n)..          sum((s),g(t,s,n))
                           - DSM_in_l(n,t)+ DSM_out_l(n,t)- DSM_in_m(n,t)+ DSM_out_m(n,t)- DSM_in_h(n,t)+ DSM_out_h(n,t)
                           + sum(st,  SOUT(st,n,t) - SIN(st,n,t))
                           + wind_max(t,n) + hydro_max(t,n) + pv_max(t,n) - q(t,n) + AC_NetInput(t,n) + DC_NetInput(t,n) =e= 0
;
gen_constraint(t,s,n)..              revision(s) * (g_max(s,n)) =g= g(t,s,n)
;
ramp_limit_constraint(t,s,n)$(ord(t) ge 1)..     ramp_limit(s,n) =g= g(t,s,n) - g(t-1,s,n)
;
ramp_up_constraint(t,s,n)$(ord(t) ge 1)..       g_up(t,s,n)  =g=   g(t,s,n) - g(t-1,s,n)
;


* LINES
AC_Constraint_LineFlow(l,t)..          AC_LineFlow(l,t) - SUM(n, PTDF(l,n) * AC_NetInput(t,n)) =e= 0
;
AC_Constraint_LineFlow_pos(l,t)..      AC_P_max(l)   =g=  AC_LineFlow(l,t)
;
AC_Constraint_LineFlow_neg(l,t)..      AC_LineFlow(l,t) =g= - AC_P_max(l)
;
AC_NetInput_Constraint(t)..            sum(n, AC_NetInput(t,n)) =e= 0
;
*DC_NetInput_Constraint(t)..           sum(n, DC_NetInput(t,n)) =e= 0
*;
DC_Constraint_LineFlow(n,t)..          DC_NetInput(t,n) - sum(dcl, DC_LineFlow(dcl,t) * DC_Incidence(dcl,n) ) =e= 0
;
DC_Constraint_LineFlow_pos(dcl,t)..    DC_P_max(dcl) =g= DC_LineFlow(dcl,t)
;
DC_Constraint_LineFlow_neg(dcl,t)..    DC_LineFlow(dcl,t) =g= - DC_P_max(dcl)
;

* STORAGE
Spowerlimit_in1(st,t,n)..              0 =g=   SIN(st,n,t)  - Sin_max(st,n)
;
Spowerlimit_out1(st,t,n)..             0 =g=   SOUT(st,n,t) - Sout_max(st,n)
;
Storage_level(st,t,n)$(ord(t) ge 2)..      S_LEVEL(st,n,t) - (S_LEVEL(st,n,t-1)  -SOUT(st,n,t) + SIN(st,n,t)* S_eff(st) )  =e= 0
;
Slimit_upper1(st,t,n)..                Scap_max(st,n) =g= S_LEVEL(st,n,t)
;
Storage_Balance(st,n,t)..              S_LEVEL(st,n,t)=g= 0
;


* DEMAND-SIDE-MANAGEMENT
DSMlimit_upper_l(t,n)..        0 =g=   DSM_in_l(n,t) - dsm_max_l(t,n)
;
DSMlimit_lower_l(t,n)..        0 =g=  DSM_out_l(n,t) - dsm_max_l(t,n)
;
DSMlimit_upper_m(t,n)..        0 =g=   DSM_in_m(n,t) - dsm_max_m(t,n)
;
DSMlimit_lower_m(t,n)..        0 =g=  DSM_out_m(n,t) - dsm_max_m(t,n)
;
```

```
DSMlimit_upper_h(t,n)..         0 =g=   DSM_in_h(n,t) - dsm_max_h(t,n)
;
DSMlimit_lower_h(t,n)..         0 =g=  DSM_out_h(n,t) - dsm_max_h(t,n)
;


DSMbalance_l(t,n)$(ord(t) ge 2).. sum(tt$((ord(tt) >= ord(t)-1) and (ord(tt)<=ord(t)+1)),
                    DSM_in_l(n,tt)-DSM_out_l(n,tt)) =e= 0
;

DSMbalance_m(t,n)$(ord(t) ge 2).. sum(tt$((ord(tt) >= ord(t)-1) and (ord(tt)<=ord(t)+1)),
                    DSM_in_m(n,tt)-DSM_out_m(n,tt)) =e= 0
;

DSMbalance_h(t,n)$(ord(t) ge 2).. sum(tt$((ord(tt) >= ord(t)-1) and (ord(tt)<=ord(t)+1)),
                    DSM_in_h(n,tt)-DSM_out_h(n,tt)) =e= 0
;


* COMBINED HEAT AND POWER
CHP_constraint_coal..           sum((t,Ger), g(t,'coal',Ger)) =g=  0.14*15.000
*0.28*sum((t,Ger),q(t,Ger))
;
CHP_constraint_lignite..        sum((t,Ger), g(t,'lignite',Ger)) =g=  0.20*15.000
*0.28*sum((t,Ger),q(t,Ger))
;
CHP_constraint_biomass..        sum((t,Ger), g(t,'biomass',Ger)) =g=  0.33*15.000
*0.28*sum((t,Ger),q(t,Ger))
;
CHP_constraint_gas_oil..        sum((t,Ger), g(t,'gas',Ger)) + sum((t,Ger), g(t,'oil',Ger)) =g=  0.27*15.000
*0.28*sum((t,Ger),q(t,Ger))
;


*------------------------------------------------------------------------------*
*       Rest                                                  *
*------------------------------------------------------------------------------*

model projektstudium2011 /all/;

g.fx(t,'Biomass',n) = revision('Biomass') * g_max('Biomass',n)     ;
S_LEVEL.fx(st,n,'t1') = 0 ;
S_LEVEL.fx('pump','NO','t1') = 0.5*Scap_max('pump','NO') ;
SOUT.up(st,n,'t1') = S_LEVEL.l(st,n,'t1');
*S_LEVEL.fx(st,n,'1008') = 0;
*S_LEVEL.lo(st,'NO','1008') = 0;

*SWITCH THE FOLLOWING FIXED VARIABLES ON AND OFF DEPENDING ON SCENARIO
*SIN.fx('battery',n,t)=0;
*SIN.fx('acaes',n,t)=0;
*SOUT.fx('battery',n,t)=0;
*SOUT.fx('acaes',n,t)=0;
*DSM_in_l.fx(n,t)=0;
*DSM_in_m.fx(n,t)=0;
*DSM_in_h.fx(n,t)=0;
*DAS gibt iwie immer comp errors


$ontext
*S_LEVEL.fx('pump','19a','t1') = Scap_max('pump','19a') ;
*S_LEVEL.fx(st,n,'t%t_max%') = 0 ;
*S_LEVEL.l('pump','19c','t%t_max%') = 1 ;
*S_LEVEL.l('pump','19a','t%t_max%') = 1 ;
$offtext

solve projektstudium2011 maximizing w using qcp;

parameter p(n,t)   Nodalpreis;
p(n,t) = - nodal_balance.m(t,n) *1 ;

Parameter total_generation(t,s);
total_generation(t,s) = sum(n, g.l(t,s,n));

Parameter total_german_generation(t,s);
total_german_generation(t,s) = sum(Ger, g.l(t,s,Ger));

Parameter total_german_demand(t);
total_german_demand(t)=sum(s,total_german_generation(t,s));

Parameter total_german_reference_demand(t);
total_german_reference_demand(t) = sum(Ger, q_ref(t,Ger));

Parameter german_renewable_share;
german_renewable_share=sum(t,sum(Ger,(g.l(t,'Biomass',Ger)+wind_max(t,Ger)+hydro_max(t,Ger)+pv_max(t,Ger))))/sum((s,t),total_german_generation(t,s))
;
```

```
Parameter full_load_hours(s);
full_load_hours(s)= sum((t,n), g.l(t,s,n))/sum(n,g_max(s,n)*card(t)*revision(s))*8760;

Parameter german_average_export_rate;
german_average_export_rate=sum(t,sum(s,total_german_generation(t,s))+sum(Ger,wind_max(t,Ger)+hydro_max(t,Ger)+pv_max(t,Ger)))/sum(t,total_german
_demand(t));

Parameter average_price(n);
average_price(n)=sum(t,p(n,t))/card(t);

Parameter german_average_price;
german_average_price=sum((t,Ger),p(Ger,t))/(card(t)*card(Ger));

Parameter total_DSM_in(n,t);
total_DSM_in(n,t)=DSM_in_l.l(n,t)+DSM_in_m.l(n,t)+DSM_in_h.l(n,t);

Parameter total_DSM_out(n,t);
total_DSM_out(n,t)=DSM_out_l.l(n,t)+DSM_out_m.l(n,t)+DSM_out_h.l(n,t);

Parameter use_rate_AC_line(l);
use_rate_AC_line(l)=sum(t, abs(AC_LineFlow.l(l,t)))/ (AC_P_max(l)*card(t));

Parameter average_use_rate_AC_line;
average_use_rate_AC_line=sum(l,use_rate_AC_line(l))/card(l);

Parameter use_rate_DC_line(dcl);
use_rate_DC_line(dcl)=sum(t, abs(DC_LineFlow.l(dcl,t)))/ (DC_P_max(dcl)*card(t));

Parameter average_use_rate_DC_line;
average_use_rate_DC_line=sum(dcl,use_rate_DC_line(dcl)/card(dcl));

Parameter congestion_shadow_cost_AC;
congestion_shadow_cost_AC=sum((l,t),AC_Constraint_LineFlow_pos.m(l,t))-sum((l,t),AC_Constraint_LineFlow_neg.m(l,t)) ;

Parameter congestion_shadow_cost_DC;
congestion_shadow_cost_DC=sum((dcl,t),DC_Constraint_LineFlow_pos.m(dcl,t))-sum((dcl,t),DC_Constraint_LineFlow_neg.m(dcl,t)) ;

Parameter AC_flow_matrix(n,nn);
AC_flow_matrix(n,nn)=sum((l,t),AC_Incidence(l,n)*AC_Incidence(l,nn)*AC_LineFlow.l(l,t));

Parameter AC_capacity_matrix(n,nn);
AC_capacity_matrix(n,nn)=sum((l),AC_Incidence(l,n)*AC_Incidence(l,nn)*AC_P_max(l)*card(t));

Parameter AC_use_rate_matrix(n,nn);
AC_use_rate_matrix(n,nn)$(AC_capacity_matrix(n,nn))=AC_flow_matrix(n,nn)/AC_capacity_matrix(n,nn);

Parameter DC_flow_matrix(n,nn);
DC_flow_matrix(n,nn)=sum((dcl,t),DC_Incidence(dcl,n)*DC_Incidence(dcl,nn)*DC_LineFlow.l(dcl,t));

Parameter DC_capacity_matrix(n,nn);
DC_capacity_matrix(n,nn)=sum((dcl),DC_Incidence(dcl,n)*DC_Incidence(dcl,nn)*DC_P_max(dcl)*card(t));

Parameter DC_use_rate_matrix(n,nn);
DC_use_rate_matrix(n,nn)$(DC_capacity_matrix(n,nn))=DC_flow_matrix(n,nn)/DC_capacity_matrix(n,nn);

Parameter AC_congestion_cost_matrix(n,nn);
AC_congestion_cost_matrix(n,nn)=sum((l,t),AC_Incidence(l,n)*AC_Incidence(l,nn)*(AC_Constraint_LineFlow_pos.m(l,t)+AC_Constraint_LineFlow_neg.m(l,t
)));
*Zaehlen der congested hours und in Knotenmatrix machen
Parameter AC_congestion_hour_matrix(n,nn);
AC_congestion_hour_matrix(n,nn)=sum((l,t),AC_Incidence(l,n)*AC_Incidence(l,nn)*(1$(AC_Constraint_LineFlow_pos.m(l,t)<-
0.1)+(1$(AC_Constraint_LineFlow_neg.m(l,t)<-0.1))));


Parameter DC_congestion_cost_matrix(n,nn);
DC_congestion_cost_matrix(n,nn)=sum((dcl,t),DC_Incidence(dcl,n)*DC_Incidence(dcl,nn)*(DC_Constraint_LineFlow_pos.m(dcl,t)+DC_Constraint_LineFlow
_neg.m(dcl,t)));

Parameter DC_congestion_hour_matrix(n,nn);
DC_congestion_hour_matrix(n,nn)=sum((dcl,t),DC_Incidence(dcl,n)*DC_Incidence(dcl,nn)*(1$(DC_Constraint_LineFlow_pos.m(dcl,t)<-
0.1)+(1$(DC_Constraint_LineFlow_neg.m(dcl,t)<-0.1))));

Parameter flow_matrix(n,nn);
flow_matrix(n,nn)=(DC_flow_matrix(n,nn)+AC_flow_matrix(n,nn))*8760/card(t);

Display DC_LineFlow.l, pv_max, hydro_max, wind_max, DC_NetInput.l, q.l,
g.l,SIN.l,SOUT.l,S_LEVEL.l,p, total_DSM_out, total_DSM_in, nodal_balance.m,
AC_Constraint_LineFlow_pos.m, AC_Constraint_LineFlow_neg.m,AC_LineFlow.l,
total_german_demand, total_german_reference_demand,w.l,german_renewable_share,german_average_export_rate,full_load_hours,
german_average_price,average_price,average_use_rate_AC_line,average_use_rate_DC_line,
congestion_shadow_cost_AC,congestion_shadow_cost_DC,use_rate_AC_line,use_rate_DC_line,
DC_use_rate_matrix,AC_use_rate_matrix,AC_congestion_cost_matrix,DC_congestion_cost_matrix,flow_matrix;


*** Write zeros in EXCEL file
g.l(t,s,n)$(not g.l(t,s,n)) = eps;
```

```
Q.l(t,n)$(not Q.l(t,n)) = eps;
P(n,t)$(not P(n,t)) = eps;
AC_Constraint_LineFlow_pos.m(l,t)$(not AC_Constraint_LineFlow_pos.m(l,t)) = eps;
AC_Constraint_LineFlow_neg.m(l,t)$(not AC_Constraint_LineFlow_neg.m(l,t)) = eps;
DC_Constraint_LineFlow_pos.m(dcl,t)$(not DC_Constraint_LineFlow_pos.m(dcl,t)) = eps;
DC_Constraint_LineFlow_neg.m(dcl,t)$(not DC_Constraint_LineFlow_neg.m(dcl,t)) = eps;
total_DSM_in(n,t)$(not total_DSM_in(n,t)) = eps;
SIN.l(st,n,t)$(not SIN.l(st,n,t)) = eps;
SOUT.l(st,n,t)$(not SOUT.l(st,n,t)) = eps;
AC_LineFlow.l(l,t)$(not AC_LineFlow.l(l,t)) = eps;
AC_NetInput.l(t,n)$(not AC_NetInput.l(t,n)) = eps;
DC_NetInput.l(t,n)$(not DC_NetInput.l(t,n)) = eps;
DC_LineFlow.l(dcl,t)$(not DC_LineFlow.l(dcl,t)) = eps;

total_generation(t,s)$(not total_generation(t,s)) = eps;
total_german_generation(t,s)$(not total_german_generation(t,s)) = eps;
pv_max(t,n)$(not pv_max(t,n)) = eps;
hydro_max(t,n)$(not hydro_max(t,n)) = eps;
wind_max(t,n)$(not wind_max(t,n)) = eps;
total_DSM_in(n,t)$(not total_DSM_in(n,t)) = eps;
AC_use_rate_matrix(n,nn)$(not AC_use_rate_matrix(n,nn))=eps;
DC_use_rate_matrix(n,nn)$(not DC_use_rate_matrix(n,nn))=eps;
AC_congestion_cost_matrix(n,nn)$(not AC_congestion_cost_matrix(n,nn))=eps;
DC_congestion_cost_matrix(n,nn)$(not DC_congestion_cost_matrix(n,nn))=eps;
AC_congestion_hour_matrix(n,nn)$(not AC_congestion_hour_matrix(n,nn))=eps;
DC_congestion_hour_matrix(n,nn)$(not DC_congestion_hour_matrix(n,nn))=eps;
flow_matrix(n,nn)$(not flow_matrix(n,nn))=eps;

*** Write output in EXCEL file
$libinclude xldump g.l output-NEP-2012.xlsx generation!b3
$libinclude xldump total_generation output-NEP-2012.xlsx total_generation!b3
$libinclude xldump total_german_generation output-NEP-2012.xlsx total_german_generation!b3
$libinclude xldump q.l output-NEP-2012.xlsx demand!b3
$libinclude xldump P output-NEP-2012.xlsx price!b3
$libinclude xldump AC_Constraint_LineFlow_neg.m output-NEP-2012.xlsx AC_Constraint_LineFlow_neg!b3
$libinclude xldump AC_Constraint_LineFlow_pos.m output-NEP-2012.xlsx AC_Constraint_LineFlow_pos!b3
$libinclude xldump DC_Constraint_LineFlow_neg.m output-NEP-2012.xlsx DC_Constraint_LineFlow_neg!b3
$libinclude xldump DC_Constraint_LineFlow_pos.m output-NEP-2012.xlsx DC_Constraint_LineFlow_pos!b3
$libinclude xldump AC_LineFlow.l output-NEP-2012.xlsx AC_LineFlow!b3
$libinclude xldump AC_NetInput.l output-NEP-2012.xlsx AC_NetInput!b3
$libinclude xldump DC_NetInput.l output-NEP-2012.xlsx DC_NetInput!b3
$libinclude xldump DC_LineFlow.l output-NEP-2012.xlsx DC_LineFlow!b3
$libinclude xldump total_DSM_in output-NEP-2012.xlsx DSM_in!b3
$libinclude xldump SIN.l output-NEP-2012.xlsx SIN!b3
$libinclude xldump SOUT.l output-NEP-2012.xlsx SOUT!b3
$libinclude xldump S_LEVEL.l output-NEP-2012.xlsx S_Level!b3
$libinclude xldump pv_max output-NEP-2012.xlsx pv_max!b3
$libinclude xldump hydro_max output-NEP-2012.xlsx hydro_max!b3
$libinclude xldump wind_max output-NEP-2012.xlsx wind_max!b3
$libinclude xldump w.l output-NEP-2012.xlsx welfare!b3
$libinclude xldump total_DSM_out output-NEP-2012.xlsx DSM_out!b3
$libinclude xldump use_rate_AC_line output-NEP-2012.xlsx use_rate_AC_line!b3
$libinclude xldump use_rate_DC_line output-NEP-2012.xlsx use_rate_DC_line!b3
$libinclude xldump AC_use_rate_matrix output-NEP-2012.xlsx use_rate_AC!a1
$libinclude xldump DC_use_rate_matrix output-NEP-2012.xlsx use_rate_DC!a1
$libinclude xldump congestion_shadow_cost_AC output-NEP-2012.xlsx congestion_cost_AC!b3
$libinclude xldump congestion_shadow_cost_DC output-NEP-2012.xlsx congestion_cost_DC!b3
$libinclude xldump AC_congestion_cost_matrix output-NEP-2012.xlsx congestion_cost_matrix_AC!a1
$libinclude xldump DC_congestion_cost_matrix output-NEP-2012.xlsx congestion_cost_matrix_DC!a1
$libinclude xldump AC_congestion_hour_matrix output-NEP-2012.xlsx congestion_hour_matrix_AC!a1
$libinclude xldump DC_congestion_hour_matrix output-NEP-2012.xlsx congestion_hour_matrix_DC!a1
$libinclude xldump flow_matrix output-NEP-2012.xlsx flow_matrix_AC_DC!a1
```

GAMS Code of the model in Chapter 7

```
*==================================================================================
* Andreas Schröder – October 2012
* Model on Grid Congestion and the effects of HVDC lines and power plant investment
* Model run requires access to the file "input-8760h.gdx"
* Input data can be obtained from the author upon request
*==================================================================================

sets
n          Node or Zone      /PT,ES,FR,NL,BE,LX,DK-
W,CH,AU,IT,PL,CZ,SK,HU,SN,CR,UA,21,22,23,24,25,26,41,42,71,72,73,74,75,76,81,82,83,84,SE,DK-E,NO,GB/
Ger(n)        Nodes in Germany   /21,22,23,24,25,26,41,42,71,72,73,74,75,76,81,82,83,84/
dcl          DC Line          /dc1*dc12,dc18*dc34,dc36*dc50/
*,dc36*dc50/
*dc51*dc52/
t          Time          /t1*t8760/
st          Storage          /pump,battery,acaes/
```

```
s               Type of plant
/
Lignite
Coal
Gas
Oil
Nuclear
Biomass
/
Flexible(s)             Subset of flexible plants /Gas,Oil/
Fossil(s)               Subset of fossil-fired plants /Coal,Gas,Nuclear/
CHP_technologies(s)     Subset of CHP-able technology plants /Coal,Gas,Nuclear,Biomass/
l                       Ordinary AC Line
/
line2
line3
line4
line6
line9
line10
line12
line13
line14
line17
line20
line21
line24
line27
line31
line34
line35
line36
line39
line40
line42
line44
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line189
line196
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line208
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line338
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line1011
line1079
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line1885
line2192
line2205
line2206
line2210
line2220
line2227
line2244
line2248
line2249
line2250
line2278
line2294
line2295
line2300
line2326
line2327
line2393
line2394
line2395
line2396
line2397
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line2404
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line2525

```
line2526
line2527
line2528
line2530
line2533
line2540
line2541
line3288
line3292
line3444
line3449
line3456
line3459
line3460
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line3469
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line3565
line3566
line3584
line3585
line3594
line3595
line3602
line3606
line3621
line3630
line3633
line3636
line3637
line3641
line3642
line3643
/
;


Alias    (t,tt),(n,nn);
option reslim = 120000000;
option iterlim = 100000000;
option
   limrow = 0,
   limcol = 0,
   solprint = off,
   sysout = off;
option savepoint=1 ;

$onecho > cplex.opt
threads 1
$offecho


*------------------------------------------------------------------------------*
* Some parameters
*------------------------------------------------------------------------------*
```

```
scalars
epsilon         Demand elasticity at reference point          / -0.1 /
loadfactor      Factor to define load levels                  / 1.0 /
windfactor      Factor to define wind generation              / 1.0 /
pvfactor        Factor to define pv generation                / 1.0 /
trm             Transmission reliability margin               / 0.2 /
c_dsm_l         DSM costs low                                 / 3   /
c_dsm_m         DSM costs medium                              / 5   /
c_dsm_h         DSM costs high                                / 10  /
;

parameter revision(s)    Factor defining the availabilty of plant types
/
Lignite  0.9
Coal     0.9
Gas      0.95
Oil      0.95
Nuclear  0.9
Biomass  0.95
/
;

display revision;

*------------------------------------------------------------------------------*
* Line parameters
*------------------------------------------------------------------------------*

Parameter
        AC_P_max(l)         Maximum Capacity of line dcl
        PTDF(l,n)           Power Transfer Distribution Factor
        AC_Incidence(l,n)   AC Incidence Matrix
        DC_P_max(dcl)       Maximum Capacity of line dcl
        DC_Incidence(dcl,n) Incidence Matrix of DC lines
;

*------------------------------------------------------------------------------*
* Generation capacities
*------------------------------------------------------------------------------*

Parameter g_max(s,n)     Generation capacities of current fossil plants;
Parameter Wind_max(t,n)  Wind generation;
Parameter PV_max(t,n)    PV generation;
Parameter Hydro_max(t,n) Hydro-electric generation;


*------------------------------------------------------------------------------*
* Reference demand  (linear demand fucntion p = a + m*q )
*------------------------------------------------------------------------------*

Parameter  q_ref(t,n)    Average demand;
Parameter  p_ref(t,n)    Reference price for demand function;

*------------------------------------------------------------------------------*
* Investment parameters
*------------------------------------------------------------------------------*

Parameter invest_cost_total(s)    Overnight investment cost in EUR per kW
/
Lignite  1700
Coal     1200
Gas      600
Oil      400
Nuclear  6000
Biomass  2300
/
;


Parameter life_length(s)    Life length of technology in years
/
Lignite  40
Coal     40
Gas      35
Oil      30
```

```
Nuclear  50
Biomass  30
/
;

Parameter invest_limit(s)    Limit for installed capacity in Europe per technology in MW accroding to Roadmap 2050 Part 1 p. 78
/
Lignite         1000000
Coal            1000000
Gas             200000
Oil             50000
Nuclear         150000
Biomass         80000
/
;

Parameter annuity_factor(s) annuity factor;
Parameter invest_cost(s) annuity or week investment cost;
Scalar r interest rate /0.09/;
annuity_factor(s) = (1+r)**(life_length(s))*r /((1+r)**(life_length(s)) - 1);
invest_cost(s) = invest_cost_total(s)*1000*annuity_factor(s)*card(t)/8760;

*------------------------------------------------------------------------------*
* Generation costs
*------------------------------------------------------------------------------*

Parameter c(s)        Erzeugungskosten der Kraftwerkstypen in EUR per MW including carbon cost
/
Lignite  66.9
Coal     68.2
Gas      75
Oil      170
Nuclear  25
Biomass  35
/
;


Parameter ramp_percentage(s)
/
Lignite  0.5
Coal     0.5
Gas      1
Oil      1
Nuclear  0.33
Biomass  1
/
;

Parameter ramp_cost(s)    marginal ramping cost
/
Lignite  60
Coal     60
Gas      10
Oil      10
Nuclear  60
Biomass  10
/
;


*------------------------------------------------------------------------------*
* Storage parameters
*------------------------------------------------------------------------------*


Parameter S_eff(st) Conversion efficiency storage
/
pump     0.75
battery  0.8
acaes    0.7
/
;

Parameter Scap_max(st,n) Storage capacity limit;
```

```
Parameter Sin_max(st,n) Storage capacity limit;

*------------------------------------------------------------------------------*
* Call GDX File
*------------------------------------------------------------------------------*

$onecho >temp.txt
par=AC_P_max     rng=AC_Capacity!A2:b263         cdim=0 rdim=1
par=PTDF         rng=PTDF!A1:AN263               cdim=1 rdim=1
par=AC_Incidence rng=AC_Capacity!m1:AZ263        cdim=1 rdim=1
par=DC_P_max     rng=DC_Capacity!A2:b45          cdim=0 rdim=1
par=DC_Incidence rng=DC_Incidence!A1:AN45        cdim=1 rdim=1
par=g_max        rng=g_max!A2:Ao8                cdim=1 rdim=1
par=Wind_max     rng=Wind!A2:AN8762              cdim=1 rdim=1
par=PV_max       rng=PV!A2:AN8762                cdim=1 rdim=1
par=Hydro_max    rng=Hydro!A2:AN8762             cdim=1 rdim=1
par=q_ref        rng=demand!A2:AN8762            cdim=1 rdim=1
par=p_ref        rng=Price!A2:AN8762             cdim=1 rdim=1
par=Scap_max     rng=storage_cap!A1:an4          cdim=1 rdim=1
par=Sin_max      rng=storage_inflow!A1:an4       cdim=1 rdim=1
$offecho

*$call GDXXRW "input-8760h.xls" @temp.txt
$gdxin input-8760h.gdx
$load AC_P_max,PTDF,AC_Incidence,DC_P_max,DC_Incidence,g_max
;
$load Wind_max,PV_max,Hydro_max,p_ref,q_ref,Scap_max,Sin_max
;


*------------------------------------------------------------------------------*
* Calculations of parameters after GDX call
*------------------------------------------------------------------------------*

AC_P_max(l) = (1-trm) * AC_P_max(l);

parameter m(t,n)                Slope of demand function;
m(t,n)$q_ref(t,n) = p_ref(t,n)/(epsilon*loadfactor*q_ref(t,n))
;

parameter a(t,n)                Intercept of demand function;
a(t,n)$q_ref(t,n) = p_ref(t,n)-loadfactor*q_ref(t,n)*m(t,n)
;

Parameter dsm_max_l(t,n)        DSM Limit;
dsm_max_l(t,n)=0.02*q_ref(t,n);

Parameter dsm_max_m(t,n)        DSM Limit;
dsm_max_m(t,n)=0.02*q_ref(t,n);

Parameter dsm_max_h(t,n)        DSM Limit;
dsm_max_h(t,n)=0.01*q_ref(t,n);

Parameter Sout_max(st,n)        Storage outflow power limit;
Sout_max(st,n) = Sin_max(st,n)
;

Parameter ramp_limit(s,n)       Ramping limits;
ramp_limit(s,n)=ramp_percentage(s)*g_max(s,n);

*------------------------------------------------------------------------------*
* Variables and equations
*------------------------------------------------------------------------------*

Variables
w                     Welfare
q_area(t)             Area under demand function
variablecost(t)       Total cost
AC_lineflow(l,t)      Lineflow on l
AC_netinput(t,n)      Net input at node n
DC_lineflow(dcl,t)    Lineflow on dcl
DC_netinput(t,n)      Net input at node n
;

Positive Variables
```

```
q(t,n)                  Demand at node n
g(t,s,n)                Generation of plant type s of firm f at node n
SIN(st,n,t)             Storage inflow
SOUT(st,n,t)            Storage outflow
g_up(t,s,n)             Generation change from one period to the next
S_LEVEL(st,n,t)         Storage level
DSM_out_l(n,t)          DSM shifting load
DSM_in_l(n,t)           DSM adding load
DSM_out_m(n,t)          DSM shifting load
DSM_in_m(n,t)           DSM adding load
DSM_out_h(n,t)          DSM shifting load
DSM_in_h(n,t)           DSM adding load
INVEST(s,n)             Investment into generation capacity
;

Equations
objective                          Zielfunktion der Maximierung (Wohlfahrtsfunktion)
nodal_balance(t,n)                 Nebenbedingung1: Erzeugung = Nachfrage + NetInput
gen_constraint(t,s,n)              Nebenbedingung3: kein Kraftwerk darf mehr Erzeugen als es kann
ramp_limit_constraint(t,s,n)       Ramping limits for power plants
ramp_up_constraint(t,s,n)          Ramping up constraint for power plants

AC_Constraint_LineFlow(l,t)        power flow for each line [MW]
AC_Constraint_LineFlow_pos(l,t)    transmission limit positive [MW]
AC_Constraint_LineFlow_neg(l,t)    transmission limit negative [MW]
AC_NetInput_Constraint(t)          Net inputs have to sum to zero over all nodes
*DC_NetInput_Constraint(t)         Net inputs have to sum to zero over all nodes
DC_Constraint_LineFlow(n,t)        power flow for each line [MW]
DC_Constraint_LineFlow_pos(dcl,t)  transmission limit positive [MW]
DC_Constraint_LineFlow_neg(dcl,t)  transmission limit negative [MW]

Spowerlimit_in1(st,t,n)            Power limit storage inflow
Spowerlimit_out1(st,t,n)           Power limit storage outflow
Storage_level(st,t,n)              Storage level at time t and node n
Slimit_upper1(st,t,n)              Capacity limit storage outflow (kann nicht mehr rein als capacity limit)
Storage_Balance(st,n,t)            Storage Balance

DSMlimit_upper_l(t,n)              Maximum of (positive) demand-side management
DSMlimit_lower_l(t,n)              Maximum of (negative) demand-side management
DSMlimit_upper_m(t,n)              Maximum of (positive) demand-side management
DSMlimit_lower_m(t,n)              Maximum of (negative) demand-side management
DSMlimit_upper_h(t,n)              Maximum of (positive) demand-side management
DSMlimit_lower_h(t,n)              Maximum of (negative) demand-side management
DSMbalance_l(t,n)                  Demand-side management balance restricts the period within which load can be shifted
DSMbalance_m(t,n)                  Demand-side management balance restricts the period within which load can be shifted
DSMbalance_h(t,n)                  Demand-side management balance restricts the period within which load can be shifted
*CHP_constraint_lignite            CHP condition for lignite
*CHP_constraint_coal               CHP condition for coal
*CHP_constraint_biomass            CHP condition for biomass
*CHP_constraint_gas_oil            CHP condition for gas and oil
Investment_constraint(s)           Upper limit potential for investments
Demand_minimum_Germany             To ensure comparability to NEP calculations
;

objective..                 w =e= ( sum(t, sum (n, (a(t,n)*q(t,n)+0.5*m(t,n)*sqr(q(t,n))))  - sum((s,n), g(t,s,n)*c(s))
                            - sum(n, c_dsm_l*DSM_out_l(n,t))-sum(n,c_dsm_m*DSM_out_m(n,t))-sum(n,c_dsm_h*DSM_out_h(n,t))
                            - sum((s,n),g_up(t,s,n)*ramp_cost(s))) -sum((s,n),invest_cost(s)*INVEST(s,n)) ) / 1
;
nodal_balance(t,n)..        sum((s),g(t,s,n))
                            - DSM_in_l(n,t)+ DSM_out_l(n,t)- DSM_in_m(n,t)+ DSM_out_m(n,t)- DSM_in_h(n,t)+ DSM_out_h(n,t)
                            + sum(st,  SOUT(st,n,t) - SIN(st,n,t))
                            + wind_max(t,n) + hydro_max(t,n) + pv_max(t,n) - q(t,n) + AC_NetInput(t,n) + DC_NetInput(t,n) =e= 0
;
gen_constraint(t,s,n)..           revision(s) * (g_max(s,n)+INVEST(s,n)) =g= g(t,s,n)
;
ramp_limit_constraint(t,s,n)$(ord(t) ge 1)..     ramp_percentage(s)*(g_max(s,n)+INVEST(s,n)) =g= g(t,s,n) - g(t-1,s,n)
;
ramp_up_constraint(t,s,n)$(ord(t) ge 1)..        g_up(t,s,n)  =g=   g(t,s,n) - g(t-1,s,n)
;


* LINES
AC_Constraint_LineFlow(l,t)..          AC_LineFlow(l,t) - SUM(n, PTDF(l,n) * AC_NetInput(t,n)) =e= 0
;
AC_Constraint_LineFlow_pos(l,t)..      AC_P_max(l)   =g=  AC_LineFlow(l,t)
```

```
;
AC_Constraint_LineFlow_neg(l,t)..      AC_LineFlow(l,t) =g= - AC_P_max(l)
;
AC_NetInput_Constraint(t)..            sum(n, AC_NetInput(t,n)) =e= 0
;
*DC_NetInput_Constraint(t)..           sum(n, DC_NetInput(t,n)) =e= 0
*;
DC_Constraint_LineFlow(n,t)..          DC_NetInput(t,n) - sum(dcl, DC_LineFlow(dcl,t) * DC_Incidence(dcl,n) ) =e= 0
;
DC_Constraint_LineFlow_pos(dcl,t)..    DC_P_max(dcl) =g= DC_LineFlow(dcl,t)
;
DC_Constraint_LineFlow_neg(dcl,t)..    DC_LineFlow(dcl,t) =g= - DC_P_max(dcl)
;

* STORAGE
Spowerlimit_in1(st,t,n)..              0 =g=   SIN(st,n,t)  - Sin_max(st,n)
;
Spowerlimit_out1(st,t,n)..             0 =g=   SOUT(st,n,t) - Sout_max(st,n)
;
Storage_level(st,t,n)$(ord(t) ge 2)..      S_LEVEL(st,n,t) - (S_LEVEL(st,n,t-1)  -SOUT(st,n,t) + SIN(st,n,t)* S_eff(st) )  =e= 0
;
Slimit_upper1(st,t,n)..                Scap_max(st,n) =g= S_LEVEL(st,n,t)
;
Storage_Balance(st,n,t)..              S_LEVEL(st,n,t)=g= 0
;


* DEMAND-SIDE-MANAGEMENT
DSMlimit_upper_l(t,n)..         0 =g=   DSM_in_l(n,t) - dsm_max_l(t,n)
;
DSMlimit_lower_l(t,n)..         0 =g=  DSM_out_l(n,t) - dsm_max_l(t,n)
;
DSMlimit_upper_m(t,n)..         0 =g=   DSM_in_m(n,t) - dsm_max_m(t,n)
;
DSMlimit_lower_m(t,n)..         0 =g=  DSM_out_m(n,t) - dsm_max_m(t,n)
;
DSMlimit_upper_h(t,n)..         0 =g=   DSM_in_h(n,t) - dsm_max_h(t,n)
;
DSMlimit_lower_h(t,n)..         0 =g=  DSM_out_h(n,t) - dsm_max_h(t,n)
;


DSMbalance_l(t,n)$(ord(t) ge 2).. sum(tt$((ord(tt) >= ord(t)-1) and (ord(tt)<=ord(t)+1)),
                        DSM_in_l(n,tt)-DSM_out_l(n,tt)) =e= 0
;

DSMbalance_m(t,n)$(ord(t) ge 2).. sum(tt$((ord(tt) >= ord(t)-1) and (ord(tt)<=ord(t)+1)),
                        DSM_in_m(n,tt)-DSM_out_m(n,tt)) =e= 0
;

DSMbalance_h(t,n)$(ord(t) ge 2).. sum(tt$((ord(tt) >= ord(t)-1) and (ord(tt)<=ord(t)+1)),
                        DSM_in_h(n,tt)-DSM_out_h(n,tt)) =e= 0
;

Investment_constraint(s)..       invest_limit(s) - sum(n, g_max(s,n) + INVEST(s,n)) =g= 0
;


$ontext
* COMBINED HEAT AND POWER
CHP_constraint_coal..            sum((t,Ger), g(t,'coal',Ger)) =g=  0.14*0.28*sum((t,Ger),q(t,Ger))
;
CHP_constraint_lignite..         sum((t,Ger), g(t,'lignite',Ger)) =g=  0.20*0.28*sum((t,Ger),q(t,Ger))
;
CHP_constraint_biomass..         sum((t,Ger), g(t,'biomass',Ger)) =g=  0.33*0.28*sum((t,Ger),q(t,Ger))
;
CHP_constraint_gas_oil..         sum((t,Ger), g(t,'gas',Ger)) + sum((t,Ger), g(t,'oil',Ger)) =g=  0.27*0.28*sum((t,Ger),q(t,Ger))
;
$offtext

Demand_minimum_Germany..         sum((t,Ger),q(t,Ger))*8760/card(t)*1/1000000 =e= 535
;

*------------------------------------------------------------------------------*
*       Solve statement and starting values
```

```
*------------------------------------------------------------------------------*

model projektstudium2011 /all/;

S_LEVEL.fx(st,n,'t1') = 0 ;
S_LEVEL.fx('pump','NO','t1') = 0.99*Scap_max('pump','NO') ;
SOUT.up(st,n,'t1') = S_LEVEL.l(st,n,'t1');
INVEST.l(s,n)=0;
INVEST.fx('Biomass',n)=0;


*SWITCH THE FOLLOWING FIXED VARIABLES ON AND OFF DEPEDNING ON SCENARIO
SIN.fx('battery',n,t)=0;
SIN.fx('acaes',n,t)=0;
SOUT.fx('battery',n,t)=0;
SOUT.fx('acaes',n,t)=0;
DSM_in_l.fx(n,t)=0;
DSM_in_m.fx(n,t)=0;
DSM_in_h.fx(n,t)=0;
INVEST.fx(s,n)=0;

*DAS gibt iwie immer comp errors

option qcp=CPLEX;
projektstudium2011.optfile=1;

solve projektstudium2011 maximizing w using qcp;

*------------------------------------------------------------------------------*
*       Write Results                                                          *
*------------------------------------------------------------------------------*

parameter p(n,t)   Nodalpreis;
p(n,t) = - nodal_balance.m(t,n) *1 ;

Parameter total_generation(t,s);
total_generation(t,s) = sum(n, g.l(t,s,n));

Parameter total_german_generation(t,s);
total_german_generation(t,s) = sum(Ger, g.l(t,s,Ger));

Parameter total_german_demand(t);
total_german_demand(t)=sum(s,total_german_generation(t,s));

Parameter total_german_reference_demand(t);
total_german_reference_demand(t) = sum(Ger, q_ref(t,Ger));

Parameter german_renewable_share Indicated as share of German generation;
german_renewable_share=sum(t,sum(Ger,(g.l(t,'Biomass',Ger)+wind_max(t,Ger)+hydro_max(t,Ger)+pv_max(t,Ger))))/sum(t,
sum(s,total_german_generation(t,s)) + sum(Ger, wind_max(t,Ger)+hydro_max(t,Ger)+pv_max(t,Ger)));

Parameter full_load_hours(s);
full_load_hours(s)= sum((t,n), g.l(t,s,n))/sum(n,(g_max(s,n)+INVEST.l(s,n))*card(t)*revision(s)+0.0001)*8760;

Parameter german_average_export_rate;
german_average_export_rate=sum(t,sum(s,total_german_generation(t,s))+sum(Ger,wind_max(t,Ger)+hydro_max(t,Ger)+pv_max(t,Ger)))/
sum(t,total_german_demand(t)+0.0001);

Parameter average_price(n);
average_price(n)=sum(t,p(n,t))/card(t);

Parameter german_average_price;
german_average_price=sum((t,Ger),p(Ger,t))/(card(t)*card(Ger));

Parameter total_DSM_in(n,t);
total_DSM_in(n,t)=DSM_in_l.l(n,t)+DSM_in_m.l(n,t)+DSM_in_h.l(n,t);

Parameter total_DSM_out(n,t);
total_DSM_out(n,t)=DSM_out_l.l(n,t)+DSM_out_m.l(n,t)+DSM_out_h.l(n,t);

Parameter use_rate_AC_line(l);
use_rate_AC_line(l)=sum(t, abs(AC_LineFlow.l(l,t)))/ (AC_P_max(l)*card(t));

Parameter average_use_rate_AC_line;
average_use_rate_AC_line=sum(l,use_rate_AC_line(l))/card(l);
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Parameter use_rate_DC_line(dcl);
use_rate_DC_line(dcl)$(DC_P_max(dcl))=sum(t, abs(DC_LineFlow.l(dcl,t)))/ (DC_P_max(dcl)*card(t));

Parameter average_use_rate_DC_line;
average_use_rate_DC_line=sum(dcl,use_rate_DC_line(dcl)/card(dcl));

Parameter congestion_shadow_cost_AC;
congestion_shadow_cost_AC=sum((l,t),AC_Constraint_LineFlow_pos.m(l,t))-sum((l,t),AC_Constraint_LineFlow_neg.m(l,t)) ;

Parameter congestion_shadow_cost_DC;
congestion_shadow_cost_DC=sum((dcl,t),DC_Constraint_LineFlow_pos.m(dcl,t))-sum((dcl,t),DC_Constraint_LineFlow_neg.m(dcl,t)) ;

Parameter AC_flow_matrix(n,nn);
AC_flow_matrix(n,nn)=sum((l,t),AC_Incidence(l,n)*AC_Incidence(l,nn)*AC_LineFlow.l(l,t));

Parameter AC_capacity_matrix(n,nn);
AC_capacity_matrix(n,nn)=sum((l),AC_Incidence(l,n)*AC_Incidence(l,nn)*AC_P_max(l)*card(t));

Parameter AC_use_rate_matrix(n,nn);
AC_use_rate_matrix(n,nn)$(AC_capacity_matrix(n,nn))=AC_flow_matrix(n,nn)/AC_capacity_matrix(n,nn);

Parameter DC_flow_matrix(n,nn);
DC_flow_matrix(n,nn)=sum((dcl,t),DC_Incidence(dcl,n)*DC_Incidence(dcl,nn)*DC_LineFlow.l(dcl,t));

Parameter DC_capacity_matrix(n,nn);
DC_capacity_matrix(n,nn)=sum((dcl),DC_Incidence(dcl,n)*DC_Incidence(dcl,nn)*DC_P_max(dcl)*card(t));

Parameter DC_use_rate_matrix(n,nn);
DC_use_rate_matrix(n,nn)$(DC_capacity_matrix(n,nn))=DC_flow_matrix(n,nn)/DC_capacity_matrix(n,nn);

Parameter AC_congestion_cost_matrix(n,nn);
AC_congestion_cost_matrix(n,nn)=sum((l,t),AC_Incidence(l,n)*AC_Incidence(l,nn)*(AC_Constraint_LineFlow_pos.m(l,t)+AC_Constraint_
LineFlow_neg.m(l,t)));

Parameter AC_congestion_hour_matrix(n,nn);
AC_congestion_hour_matrix(n,nn)=sum((l,t),AC_Incidence(l,n)*AC_Incidence(l,nn)*(1$(AC_Constraint_LineFlow_pos.m(l,t)<-
0.1)+(1$(AC_Constraint_LineFlow_neg.m(l,t)<-0.1))));


Parameter DC_congestion_cost_matrix(n,nn);
DC_congestion_cost_matrix(n,nn)=sum((dcl,t),DC_Incidence(dcl,n)*DC_Incidence(dcl,nn)*(DC_Constraint_LineFlow_pos.m(dcl,t)+DC_
Constraint_LineFlow_neg.m(dcl,t)));

Parameter DC_congestion_hour_matrix(n,nn);
DC_congestion_hour_matrix(n,nn)=sum((dcl,t),DC_Incidence(dcl,n)*DC_Incidence(dcl,nn)*(1$(DC_Constraint_LineFlow_pos.m(dcl,t)<-
0.1)+(1$(DC_Constraint_LineFlow_neg.m(dcl,t)<-0.1))));

Parameter flow_matrix(n,nn);
flow_matrix(n,nn)=(DC_flow_matrix(n,nn)+AC_flow_matrix(n,nn))*8760/card(t);

Parameter Yearly_Production_TWh(n);
Yearly_Production_TWh(n)=sum(t,sum(s,g.l(t,s,n))+wind_max(t,n)+hydro_max(t,n)+pv_max(t,n))*8760/card(t)*1/1000000;

Parameter Yearly_Demand_TWh(n);
Yearly_Demand_TWh(n)=sum(t,q.l(t,n))*8760/card(t)*1/1000000;

Display w.l,german_renewable_share,german_average_export_rate,full_load_hours,Yearly_Production_TWh,Yearly_Demand_TWh,
german_average_price,average_price,average_use_rate_AC_line,average_use_rate_DC_line,
DC_use_rate_matrix,AC_use_rate_matrix,AC_congestion_cost_matrix,DC_congestion_cost_matrix,flow_matrix
INVEST.l,invest_cost;


*** Write zeros
g.l(t,s,n)$(not g.l(t,s,n)) = eps;
Q.l(t,n)$(not Q.l(t,n)) = eps;
P(n,t)$(not P(n,t)) = eps;
AC_Constraint_LineFlow_pos.m(l,t)$(not AC_Constraint_LineFlow_pos.m(l,t)) = eps;
AC_Constraint_LineFlow_neg.m(l,t)$(not AC_Constraint_LineFlow_neg.m(l,t)) = eps;
DC_Constraint_LineFlow_pos.m(dcl,t)$(not DC_Constraint_LineFlow_pos.m(dcl,t)) = eps;
DC_Constraint_LineFlow_neg.m(dcl,t)$(not DC_Constraint_LineFlow_neg.m(dcl,t)) = eps;
total_DSM_in(n,t)$(not total_DSM_in(n,t)) = eps;
SIN.l(st,n,t)$(not SIN.l(st,n,t)) = eps;
SOUT.l(st,n,t)$(not SOUT.l(st,n,t)) = eps;
AC_LineFlow.l(l,t)$(not AC_LineFlow.l(l,t)) = eps;
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AC_NetInput.l(t,n)$(not AC_NetInput.l(t,n)) = eps;
DC_NetInput.l(t,n)$(not DC_NetInput.l(t,n)) = eps;
DC_LineFlow.l(dcl,t)$(not DC_LineFlow.l(dcl,t)) = eps;

total_generation(t,s)$(not total_generation(t,s)) = eps;
total_german_generation(t,s)$(not total_german_generation(t,s)) = eps;
pv_max(t,n)$(not pv_max(t,n)) = eps;
hydro_max(t,n)$(not hydro_max(t,n)) = eps;
wind_max(t,n)$(not wind_max(t,n)) = eps;
total_DSM_in(n,t)$(not total_DSM_in(n,t)) = eps;
AC_use_rate_matrix(n,nn)$(not AC_use_rate_matrix(n,nn))=eps;
DC_use_rate_matrix(n,nn)$(not DC_use_rate_matrix(n,nn))=eps;
AC_congestion_cost_matrix(n,nn)$(not AC_congestion_cost_matrix(n,nn))=eps;
DC_congestion_cost_matrix(n,nn)$(not DC_congestion_cost_matrix(n,nn))=eps;
AC_congestion_hour_matrix(n,nn)$(not AC_congestion_hour_matrix(n,nn))=eps;
DC_congestion_hour_matrix(n,nn)$(not DC_congestion_hour_matrix(n,nn))=eps;
flow_matrix(n,nn)$(not flow_matrix(n,nn))=eps;
INVEST.l(s,n)$(not INVEST.l(s,n))=eps;


execute_unload "results-8760h.gdx"
german_renewable_share,german_average_export_rate,full_load_hours,Yearly_Production_TWh,Yearly_Demand_TWh,
german_average_price,average_price,average_use_rate_AC_line,average_use_rate_DC_line,
DC_LineFlow,g,total_generation,total_german_generation,q,P,total_DSM_in,SIN,SOUT,
S_LEVEL,pv_max,hydro_max,wind_max,w,total_DSM_out,use_rate_AC_line,use_rate_DC_line,
AC_use_rate_matrix,DC_use_rate_matrix,congestion_shadow_cost_AC,congestion_shadow_cost_DC,
AC_congestion_cost_matrix,DC_congestion_cost_matrix,AC_congestion_hour_matrix,DC_congestion_hour_matrix,
flow_matrix,INVEST,invest_cost
;
```