The costs of electricity systems with a high share of fluctuating renewables - a stochastic investment and dispatch optimization model for Europe

AUTOREN

Stephan Nagl

Michaela Fürsch

Dietmar Lindenberger

EWI Working Paper, No 01/2012

www.ewi.uni-koeln.de

The costs of electricity systems with a high share of fluctutating renewables - a stochastic investment and dispatch optimization model for Europe☆

Stephan Nagl[a,*], Michaela Fürsch[a], Dietmar Lindenberger[a]

[a] *Institute of Energy Economics, University of Cologne, Vogelsanger Strasse 321, 50827 Cologne, Germany*

Abstract

Renewable energies are meant to produce a large share of the future electricity demand. However, the availability of wind and solar power depends on local weather conditions and therefore weather characteristics must be considered when optimizing the future electricity mix. In this article we analyze the impact of the stochastic availability of wind and solar energy on the cost-minimal power plant mix and the related total system costs. To determine optimal conventional, renewable and storage capacities for different shares of renewables, we apply a stochastic investment and dispatch optimization model to the European electricity market. The model considers stochastic feed-in structures and full load hours of wind and solar technologies and different correlations between regions and technologies. Key findings include the overestimation of fluctuating renewables and underestimation of total system costs compared to deterministic investment and dispatch models. Furthermore, solar technologies are - relative to wind turbines - underestimated when neglecting negative correlations between wind speeds and solar radiation.

Keywords: Stochastic programming, electricity, renewable energy

JEL classification: C61, C63, Q40

ISSN: 1862-3808

☆The authors would like to thank Stefan Thoenes for his helpful suggestions. This paper also benefited from comments by the participants of the 34th International IAEE Conference in Stockholm (Sweden), June 2011 and the research seminar of the Institute of Energy Economics at the University of Cologne in 2011.

*Corresponding author

Email address: `Stephan.Nagl@uni-koeln.de, +49 22127729210` (Stephan Nagl)

1. Introduction

As an attempt to fight global warming, many countries try to reduce CO_2 emissions from electricity generation by significantly increasing the proportion of renewables (RES-E). The cost-efficient transformation from a fossil fuel based to a primarily renewable based electricity system is often analyzed by applying deterministic investment and dispatch models for single countries or regions. Model results often suggest that wind power, photovoltaics (PV) and biomass will replace fossil fuel generation and total system costs will only moderately increase due to assumed cost reductions for renewable energies.

However, even considering significant capital cost reductions for renewables these model results may be questioned because unlike conventional or nuclear power plants the availability of fluctuating renewables such as wind and PV power depends on local weather conditions and is therefore stochastic. The availability may or may not be favorable in terms of meeting the hourly electricity demand and weather situations such as longer timeframes with e.g. minimal wind power feed-in need to be considered. Deterministic investment and dispatch models do not capture the uncertainty about the availability of fluctuating renewables by modeling the dispatch for a few days with typical feed-in structures[1], average full load hours and average correlations between wind and solar availability.

As regional wind speeds and solar radiation differ significantly between years, the amount of yearly generated electricity by wind turbines and solar panels is uncertain. Due to the existence of positive and negative availability correlations between technologies (e.g. negative correlation between PV and wind power) and between regions (e.g. wind in Great Britain and Italy) a mix of wind and solar technologies as well as geographical distributed RES-E capacities is often suggested to hedge against this uncertainty (Heide et al., 2010). However, also the extent of the correlation between technologies and between regions differs between years and is therefore uncertain. Table 1 illustrates the uncertain availability and the negative correlation between wind and solar feed-in on a yearly basis.[2] Due to these uncertainties, the optimal capacity mix might be different than determined in deterministic investment and dispatch models and total system costs for high RES-E systems might be significantly higher than estimated so far.

[1] Some models neglect ramp-up constraints and optimize the capacity mix and generation for a given load duration curve.

[2] The calculations are based on wind speeds and global radiation data from EuroWind (2011) and suppose a 5.04 MW wind turbine and a state-of-the-art 5 kW solar panel.

Table 1: Full load hours of wind and solar technologies in Europe from 2006 to 2010

	UK-C		IB-S		DE-C		FR-S	
	Wind	PV	Wind	PV	Wind	PV	Wind	PV
2006	3,731	-	1,651	-	1,918	-	2,131	-
2007	3,781	824	1,893	1,395	2,380	813	2,461	1,198
2008	3,917	835	2,064	1,419	2,105	867	2,405	1,132
2009	3,416	879	1,898	1,418	1,792	837	2,433	1,202
2010	2,924	882	2,106	1,366	1,441	878	2,460	1,163

In this paper, we try to quantify the additional system costs and the impact on the cost-efficient capacity mix when accounting for the uncertainty about the availability of wind and solar plants. We develop a stochastic investment and dispatch optimization model which considers uncertainty about the hourly and yearly availability of wind and solar resources[3] and apply it to the European electricty market.[4] The stochastic feed-in of wind and solar power technologies as well as stochastic full load hours are taken into account by different feed-in structures reflecting the empirical data. The resulting electricity mix is a robust solution for the cost-efficient electricity mix and gives a better idea of the related total system costs.

We find that fluctuating renewables are overvalued in deterministic optimization models and hence, dispatchable renewable energies such as biomass or geothermal sites - even considering high investment or fuel costs - are underestimated in high RES-E scenarios. Furthermore, solar technologies are - relative to wind power - underestimated when neglecting the negative correlation between wind and solar power. The results also indicate that the total system costs for high RES-E electricity systems are significantly underestimated when neglecting the stochastic availability of wind and solar technologies. The cost difference increases with a higher share of fluctuating RES-E generation and amounts to 35.5 bn. €$_{2010}$ which represents about 12.5 % of the total system costs in case of a 95 % RES-E quota.

The remainder of the paper is structured as follows: Section 2 sketches literature of models which account for the stochastic availability of wind and solar power. In Section 3, a bootstrap approach is presented to generate Europe-wide combined regional wind and solar feed-in structures. In Section 4, the stochastic optimization model is presented and model results are discussed. Conclusions are drawn in Section 5 providing an outlook of further possible research.

[3]For clarification, we assume perfect foresight within each dispatch realization as such short term uncertainties e.g. short noticed power plant outages or forecast errors are not modeled and therefore system costs are higher in reality.

[4]We devide Europe in several zones in order to limit computational times: United Kingdom (UK), France (FR), Benelux (LU), Iberian Peninsula (IB), Italy (IT), Austria (AT), Switzerland (CH), Germany (DE), Denmark (DK), Skandinavia (SK), Poland (PL), Czech Republic (CZ) and Eastern Europe (ET).

2. Literature review and contributions of the current work

Several models have been developed to identify the optimal combinations of renewable and conventional resources on a large scale. Short et al. (2003) divide the United States into 356 wind regions, and model the cost-efficient installations and operation of wind farms and conventional generators from 2000 through 2050. DeCarolis and Keith (2006) develop an optimization model for one investment period in 2020 based on 5 years of hourly wind and load data. Considering the assumed costs of wind turbines, the simulation indicates that supplying 50 % of the electricity demand by wind power adds about 1-2 ct/kWh to the costs of electricity generation. Neuhoff et al. (2008) divide the United Kingdom into 7 regions and optimize investments and dispatch choices for new and existing natural gas, coal and wind generators during four 5-year investment periods. The SWITCH model at the University of California, Berkeley (Fripp, 2008) concentrates on California and optimizes the combination of more than 229 wind, 464 solar sites and conventional resources considering investment and operational costs. Heide et al. (2010) model the optimal mix of wind and PV capacities for Europe by minimizing needed storage capacities subject to the constraint that all renewable energy is used (independent of total system costs). In case of supplying 100 % electricity by wind and solar technologies, the optimal mix is found to be 55 % wind and 45 % solar power generation. The DIMENSION model of the Institute of Energy Economics at the University of Cologne (EWI, 2011) simulates in 5-year time steps the cost-efficient European capacity development and dispatch for twelve typical days of conventional, renewable and storage technologies until 2050. Different regional conditions for RES-E capacites are considered by modeling 47 wind onshore, 42 wind offshore and 38 solar regions. Due to modeling deterministic feed-in structures and average full load hours of wind and solar technologies, all of these models neglect the uncertainty about the hourly availability of renewable energy.

Methodologies incorporating uncertainty in optimization models were developed by Dantzig (1955). They were applied to electricity generation planning problems to analyze the impact of demand uncertainty for the first time in the 1980s (Murphy et al., 1982; Modiano, 1987). A broad overview of different stochastic modeling approaches for electricity markets is given in Möst and Keles (2010). The economic value of wind power, taking into account the volatility of wind velocity, was analyzed by Beenstock (1995). The method is based on the intuition that one can immunize the output of a wind turbine against fluctuations in wind speed by investing in back-up capacities and the costs of necessary back-up investments may be regarded as the costs of wind volatility. Papaefthymiou et al. (2006) present a Monte-Carlo simulation technique to model the extremes of stochastic wind generation in power systems by sampling wind turbines with similar generation patterns. Swider and Weber (2006) apply a stochastic fundamental electricity market model to estimate the integration costs of wind due to the changed system operation and investments in Germany. The simulation indicates that the value of fluctuating renewables is overestimated applying a static, deterministic model. In particular, investment planning under uncertainty considering power plant outages and fluctuating renewable feed-in was analyzed in Sun et al. (2008). By applying a stochastic mixed-integer optimization model for power plant investment planning to the German electricity market, Sun et al. (2008) show how ignoring short term uncertainties significantly undervalues the needed operational flexibility and can result in insufficient investments. However, in these models the deployment of RES-E capacities is not part of the optimization problem and therefore the optimal mix of conventional, nuclear, storage and renewable technologies in high RES-E scenarios was not determined.

In this paper, we present a stochastic investment and dispatch optimization model for electricity markets that accounts for the uncertain feed-in of wind and solar technologies to determine the optimal mix of conventional, renewable and storage capacities for different European RES-E targets. To our knowledge, a stochastic electricity market model with as much detail concerning the different local RES-E conditions and the uncertain feed-in of fluctuating renewables has not appeared before. The difference between the stochastic model results and the deterministic solution based on averages in wind speeds and solar radiation can be interpreted as the impact of the stochastic availability of wind and solar power.

3. Generation of combined wind and solar feed-in structures

Wind and solar technologies are meant to produce a large share of the future electricity demand. However, the availability of these technologies depends on local weather conditions and therefore weather characteristics must be considered when optimizing the future electricity mix. Regional weather characteristics lead to different local RES-E conditions throughout Europe (higher solar radiation in Southern Europe and stronger winds in Northern Europe), to stochastic amounts of yearly generated electricity of wind and solar sites as well as to positive or negative correlations between the availabilty in different regions or between technologies. In this section, we describe the characteristics of wind speeds and solar radiation in Europe (subsection 3.1), a bootstrap approach to create consistent regional wind and solar feed-in structures and a heuristic to select representative feed-in structures as input parameters for the stochastic optimization model (subsection 3.2).

3.1. Empirical data for wind speeds and solar radiation in Europe

The description of wind speed (subsection 3.1.1) and solar radiation (subsection 3.1.2) characteristics for different regions throughout Europe is based on hourly wind speed and solar radiation data from EuroWind for the years 2006-2010 and includes an analysis of the regional correlations between wind speeds (and solar radiation) in Europe as well as the correlation between wind and solar power (subsection 3.1.3). The hourly wind speed data in 30 meters above ground and solar radiation for 64 European regions the years 2006-2010 provide a deep insight of the characteristics of regional wind speed and solar radiation in Europe as well as the correlation between wind speed and solar radiation.[5] In the following the different conditions throughout Europe are discussed for some of the selected regions. The numerical data for all regions can be found in Appendix B.

3.1.1. Characteristics of wind speeds

Wind speed distributions reflect that in most regions strong winds are rare and that moderate winds occur most often. Due to seasonal characteristics the average wind speed is usually higher in winter and autumn as in the summer months. Table 2 shows summarizing statistics for some of the selected wind regions in Europe. As wind speeds are usually higher in Northern Europe, the average wind speed in 30 meters was 6.74 m/s in Northern Ireland compared to 3.59 m/s in Southern Italy for the years 2006-2010. Higher wind speeds often result in a higher variance as can be seen by comparing the variance of the wind speed in the Southern part of the Iberian Peninsula (9.02) and offshore wind in the United Kingdom (18.81). Due to generally short distances between European regions the same general weather situations occur. Hence, the hourly wind speeds in Europe are to some extent correlated. Table 3 shows the Pearson correlation factors for some of the selected wind regions in Europe. This sample shows that closer regions have a stronger correlation, e.g. 0.587 between on- and offshore wind in the United Kingdom. However, some wind regions in Europe are not or negatively correlated (e.g. United Kingdom and Iberian Peninsula).

Table 2: Summarizing statistics for some of the selected wind regions

	UK-W (on)	IB-S (on)	DE-C (on)	PL-N (on)	IT-S (on)	UK-N (off)	IB-W (off)
Mean [m/s]	6.74	4.80	4.89	6.33	3.59	8.82	5.03
- summer [m/s]	5.95	4.40	4.38	5.49	3.44	7.45	4.52
- winter [m/s]	7.65	5.03	5.47	7.22	3.67	10.26	5.30
Median [m/s]	6.28	4.12	4.54	5.92	3.10	8.28	4.27
Variance	10.48	9.02	5.51	9.24	4.34	18.81	10.23
10%-Quantil	2.97	1.73	2.18	2.80	1.42	3.55	1.71
90%-Quantil	11.15	8.90	8.13	10.36	6.48	14.85	9.60

[5] Meteorological data for 242 measure stations of the German Weather Service for the years 2000-2010 and the European solar radiation from Satel-Light for the years 1996-2000 confirms the listed characteristics in the dataset from EuroWind.

Table 3: Correlation matrix for some of the selected wind regions (full table in the Appendix B)

	UK-W (on)	IB-S (on)	DE-C (on)	PL-N (on)	IT-S (on)	UK-N (off)	IB-W (off)
UK-W (on)	1						
IB-S (on)	-0.026	1					
DE-C (on)	0.204	-0.031	1				
PL-N (on)	0.143	-0.014	0.289	1			
IT-S (on)	0.085	0.137	0.171	0.029	1		
UK-N (off)	0.587	-0.053	0.298	0.178	-0.002	1	
IB-W (off)	-0.025	0.922	-0.024	-0.006	0.239	-0.039	1
IT-W (off)	0.027	0.365	0.096	0.003	0.327	0.028	0.303

The values in Table 2 and Table 3 represent the average of several years. However, as weather situations differ between years, the yearly average wind speed varies as well. Table 4 depicts the yearly average wind speed for the years 2006 to 2010. The average wind speed in the United Kingdom in 2008 was significantly higher with 7.26 m/s than the 5.93 m/s in 2010. Even considering the small dataset, the difference of more than 1 m/s represents about 20 % of the average over the five years. Similar to the yearly average wind speed, the correlation between wind regions differs as well. The Pearson correlation factor for wind in the United Kingdom of 0.58 in 2006 indicates a rather strong correlation but with 0.45 in 2010 the correlation can also be lower. Naturally, data for five years does not represent the long term average of wind speeds as it does not capture the variance between years sufficienctly.

Table 4: Difference between wind years: 2006-2010

	UK-W (on)	IB-S (on)	DE-C (on)	PL-N (on)	IT-S (on)	UK-N (off)	IB-W (off)
Mean [m/s]							
2006	6.90	4.49	4.86	6.07	3.49	8.80	4.81
2007	6.73	4.72	5.35	6.74	3.50	9.04	4.95
2008	7.26	4.94	5.08	6.66	3.63	9.54	5.19
2009	6.89	4.75	4.81	6.15	3.69	8.97	4.97
2010	5.93	5.11	4.34	6.03	3.61	7.74	5.26

Based on the described wind characteristics three aspects influcence the optimal electricity mix: First, from a system perspective it might be cost-efficient to focus on the best European sites i.e. with the highest full load hours on average. The data suggests that on average more than twice as much electricity can be produced from the same turbine in Ireland than in Italy. As installation costs are similar over Europe, levelized electricity costs for wind power are about 50 percent lower in Northern Europe as in Southern Europe at relatively similar conditions. Second, in particular in electricity systems with a high share of fluctuating RES-E generation a distribution of wind turbines might be cost-efficient as the hourly European-wide total power generation from wind turbines would be more stable. Third, the optimal electricity mix has to consider an uncertainty about the yearly availabilty of wind power - resulting from high as well as low wind years. Hence, there should exist an optimum between focusing on the best sites and a distribution throughout Europe.

3.1.2. Characteristics of solar radiation

Global radiation depends on the location, daytime, season and local weather conditions. Hence, the yearly radiation in Southern Europe is higher than in Northern Europe and the average solar radiation is generally higher in summer than winter. The times of sunrise and sunset also depend on the season and hence the duration of daily solar radiation varies throughout the year. Regional weather conditions such as cloudiness or wind significantly influence the solar radiation. Table 5 shows summarizing statistics for some of the analyzed solar regions in Europe. Due to the same general weather conditions in Europe, solar radiation in different European regions is correlated on an hourly basis. Table 6 shows the Pearson correlation factors for some of the selected solar regions in Europe (only daytime hours). Due to the distinguished solar structure with a peak at midday, the Pearson factors are rather high. This sample shows that some regions have a stronger correlation, e.g. 0.730 between Southern France and Southern Italy compared to 0.643 between Poland and the United Kingdom.

Table 5: Summarizing statistics for some of the selected solar regions

	UK-C	IB-S	FR-S	DE-C	SK-S	PL-N	IT-S
Mean [W/m^2]	139	228	191	138	138	152	214
- summer [W/m^2]	231	314	283	233	247	250	309
- winter [W/m^2]	75	172	130	70	61	81	150
Maximum [W/m^2]	953	1,021	997	909	834	886	976
Variance	44,884	88,594	68,087	44,537	43,124	48,356	75,138
90%-Quantil	490	746	575	496	497	534	690

Table 6: Correlation matrix for some of the selected solar regions - daytime (full table in Appendix B)

	UK-C	IB-S	FR-S	DE-C	SK-S	PL-N	IT-S
UK-C	1						
IB-S	0.709	1					
FR-S	0.717	0.783	1				
DE-C	0.707	0.654	0.688	1			
SK-S	0.715	0.646	0.713	0.763	1		
PL-N	0.643	0.584	0.603	0.714	0.746	1	
IT-S	0.653	0.670	0.730	0.683	0.728	0.703	1

The values in Table 5 and Table 6 represent the average of several years. However, the yearly average solar radiation varies between the years. Table 7 depicts the yearly average solar radiation for the years 2007 to 2010. Average solar radiation of 222 W/m^2 in Italy in 2008 was significantly higher than the 206 W/m^2 in 2010. Even considering the small dataset, the difference of more than 16 W/m^2 represents about 7 % of the average over the four years. Similar to the yearly average solar radiation, the correlation between solar regions differs as well. The Pearson correlation factor between the hourly solar radiation in Southern France and Southern Italy of 0.86 in 2008 indicates a strong correlation but with 0.80 in 2007 the correlation can also be lower in a specific year. Naturally, data for four years does not represent the long term average of solar radiation as it does not capture the variance between years.

Table 7: Difference between solar years: 2007-2010

	UK-C	IB-S	FR-S	DE-C	SK-S	PL-N	IT-S
Mean [W/m^2]							
2007	134	228	195	133	135	154	213
2008	136	231	185	141	141	149	222
2009	143	231	196	137	141	156	213
2010	144	223	190	143	133	149	206

The optimal regional allocation of solar technologies follows the same concept as for wind turbines. Due to better conditions solar technologies might be cost-efficient in Southern rather than in Northern Europe. However, a large deployment of solar technologies in one region might lead to a very unbalanced availability of solar power in the system. A regional concentration might also need significant grid extensions from solar sites to large load centers.

3.1.3. Correlation of wind speeds and solar radiation

Solar radiation and wind speeds are influenced by similar local weather characteristics such as air pressure, sunshine, degree of cloudiness or rain. As higher wind speeds usually occur when the sky is cloudy and sunshine is low, wind speed and solar radiation are to some extent negatively correlated. Table 8 shows the correlation factors between wind speed and solar radiation for the years 2006-2010 at daytime. The data reflects that solar radiation and wind speed within the same region are negatively correlated with a Pearson correlation factor between -0.004 in Iberian Peninsula (north) and -0.231 in the United Kingdom (central).

Table 8: Correlation matrix of wind and solar radiation for some selected regions - daytime (full table in Appendix B)

		Wind							
		UK-C	IB-N	IB-S	FR-S	DE-C	PL-N	CZ-C	IT-N
Solar	UK-C	-0.230	-0.053	-0.187	-0.195	-0.098	-0.137	-0.008	0.065
	IB-N	-0.176	-0.045	-0.200	-0.163	-0.043	-0.090	0.013	0.069
	IB-S	-0.158	-0.057	-0.140	-0.096	0.018	-0.093	0.045	0.043
	FR-S	-0.164	-0.107	-0.192	-0.231	-0.040	-0.076	0.026	0.026
	DE-C	-0.209	-0.070	-0.211	-0.232	-0.228	-0.150	-0.148	0.011
	PL-N	-0.195	-0.105	-0.182	-0.190	-0.124	-0.141	-0.156	-0.032
	CZ-C	-0.196	-0.086	-0.195	-0.191	-0.184	-0.159	-0.198	-0.004
	IT-N	-0.189	-0.139	-0.219	-0.248	-0.102	-0.104	-0.069	-0.147

However, the extent of the negative correlation between the availability of wind and solar power differs between years. Table 9 depicts the different correlation factors for hourly wind speed and solar radiation for the years 2007 to 2010. As can be seen for the example of Poland the Pearson correlation factors vary between -0.077 (2009) and -0.188 (2008) among these years.

Table 9: Extent of the negative correlation between wind and solar for the years 2007-2010 - daytime

	UK-C	IB-N	FR-S	DE-C	PL-N	CZ-C	IT-N
2007	-0.186	0.035	-0.146	-0.278	-0.162	-0.233	-0.224
2008	-0.241	-0.021	-0.214	-0.196	-0.188	-0.243	-0.205
2009	-0.221	-0.108	-0.290	-0.215	-0.077	-0.106	-0.289
2010	-0.270	-0.083	-0.284	-0.212	-0.135	-0.206	-0.353

3.2. Extraction of feed-in structures from the data

In subsection 3.1, the characteristics of wind and solar availability for Europe were discussed and their influence on the optimal electricity mix indicated. On the one hand long term average wind speed and solar power as well as average correlations are important for the determination of the optimal electricity mix. On the other hand characteristics such as the yearly availability or correlations can significantly vary between years and the optimal electricity mix can only be determined by accounting for these variations.

As the empirical data of combined wind and solar availability is available for five years for this analysis, we only have an indication about the variance for yearly full load hours for each region and for the yearly correlation between regions or technologies. Therefore, we use a bootstrapping approach to estimate the variance of yearly full load hours as well as the correlations between regions and technologies. A selection of the created possible feed-in structures are used as input data for the optimization model. The bootstrap approach is a resampling method which can be used to assess the properties of a distribution underlying a sample and the parameters of interest that are derived from this distribution (Efron, 1979). As a necessary condition for the bootstrap method, the original data needs to reflect the underlying distribution. This leads to two critical assumtions for this analysis: First, we assume that the hourly data for wind speeds and solar radiation of five years represents the full spectrum of possible weather situations. Second, as we create consistent wind and solar structures for a future year, we need to assume that weather conditions will stay similar as today. It is clear that the data does not contain all possible weather situations in Europe but it can be assumed that five years of hourly wind speed and solar radiation give a broad spectrum. Taking into account the effects of climate change on stochastic regional solar and wind availabilities in energy optimization models clearly remains a challenge, but is beyond the scope of this paper.

As a first step we generate 2000 different feed-in structures based on the provided wind speed and solar radiation data for the years 2006 to 2010 (subsection 3.2.1). Ideally, all these could be used as input parameters in the stochastic optimization model considering their relative probability. Due to computational contraints for the optimization problem we will select representative feed-in structures for wind and solar technologies throughout Europe (subsection 3.2.2).

3.2.1. Bootstrap approach to generate combined wind and solar feed-in strucures

To account for the above described seasonal characteristics for wind and solar availability, we divide the dataset in two blocks: months from April to August as spring and summer; months from September to March as autumn and winter. We randomly pick 30 days of consistent wind and solar radiation data over all regions in three day-blocks from the dataset and repeat this 2000 times.[6] By taking blocks rather than single hours, typical hourly changes and daily structures of wind speeds and solar radiation are reflected. Another advantage of picking blocks rather than single days is that common general weather situations such as a storm traveling from Western to Eastern Europe are to some extent considered. Naturally, due to picking three day blocks common weather situations which last for more than three days are not reflected in the bootstrapped data.[7] The possible feed-in of wind power and PV sites in different regions in Europe is computed based on the hourly wind speed and solar radiation of the 30 days (720 hours) as well as the technical parameters of wind and solar technologies. Future state-of-the-art wind and solar technologies are assumed to have the technical properties shown in Table 10.

[6] Due to computational constraints the dispatch in the optimization model is simulated for 720 instead of 8760 hours. To account for the seasonal differences we pick 9 autumn/winter; 12 spring/summer and again 9 autumn/winter days.

[7] As solar radiation is zero at night, the change from one block to another does not induce an unrealistic change of solar radiation at midnight. The situation is different for wind speeds and therefore we average wind speeds for the hours between 21 pm to 3 am to smooth the break around midnight. We find that taking the moving average of four hours leads to a realistic change of wind speeds.

Table 10: Assumed state-of-the-art wind and solar technologies

Technology	Capacity [MW]	Efficiency [%]	Area [km^2]	Height [m]	Radius [m]
Wind turbine	8	80	0.423	140	65
PV ground	1	14			
PV roof	0.005	14			

To scale wind speeds from 30 meters to the assumed turbine height, the standard logarithmic conversion is used. The conversion of wind speeds in reference height to turbine height are computated by a scaling factor which is a function of turbine height, reference height and the roughness parameter of the region. The roughness parameter takes the different surface conditions into account.[8]

$$v_{normh}(reg,h,s) = v(reg,h,s) \cdot \left[\ln \frac{normh(tech)}{rough(reg)} \Big/ \ln \frac{refh}{rough(reg)} \right] \tag{1}$$

The power generation of wind turbines is calculated as a ratio of the installed capacity of the specific wind turbine.[9] Power output is a function of air density, rotor area, power coefficient, wind speed and efficiency. A typical power curve for wind turbines (pitch control) is assumed with no generation at wind speeds lower than 3 m/s and a shutdown at more than 25 m/s to avoid damages. The power generation by the assumed state-of-the-art photovoltaic system is computed based on the net efficiency, the surface area and solar radiation. This implies standard configurations of PV systems directed towards the South and with an angle of 30 degrees in order to achieve the highest yearly energy output.

$$P_{el}(reg,tech,h,s) = 1/P_{nom}(tech) \cdot 1/2 \cdot \rho \cdot \pi \cdot r^2(tech) \cdot v^3(reg,h,s) \cdot \eta_{total} \tag{2}$$

$$P_{el}(reg,tech,h,s) = 1/P_{nom}(tech) \cdot \eta_{total}(tech) \cdot A(tech) \cdot radiation(reg,h,s) \tag{3}$$

The resulting regional wind speed and solar radiation structures have the characteristics shown in Table 11. When comparing the wind speed and solar radiation to the original data reflected in Table 2 and 5, we find similar wind speed and solar radiation characteristics. Hence, we argue that this approach provides consistent feed-in structures of wind and solar technologies for several European regions.

[8] Alternatively, the Hellmann height conversion formula could be used to scale wind speeds to different heights: $v(h,s) = v_{refh}(h,s) \cdot [\frac{h}{refh}]^{\alpha_{Hell}}$. Typical Hellman coefficients α_{Hell} are in the range of 0.06 to 0.60 (Hsu, 1988).

[9] As we use a linear optimization model, any linear combination of technologies can be realized. Therefore all capacities are normalized to 1 MW units.

Table 11: Summarizing statistics for created wind speeds and solar radiation for some of the selected regions

Wind [m/s]	UK-W (on)	IB-S (on)	DE-C (on)	PL-N (on)	IT-S (on)	UK-N (off)	IB-W (off)
Mean	6.8	4.9	5.0	6.6	5.2	9.0	5.1
Median	6.3	4.2	4.7	6.2	4.5	8.5	4.3
Variance	10.9	9.6	5.9	9.7	8.9	18.9	10.9
Solar [W/m^2]	UK-C	IB-S	FR-S	DE-C	SK-S	PL-N	IT-S
Mean	131	222	184	132	130	146	209
Median	21	55	38	23	22	33	69
Variance	41,327	85,413	65,041	42,059	40,716	45,471	72,042

Figure 1 depicts the distribution of full load hours for two solar (Southern part of the Iberian Peninsula and Northern Germany) and two wind regions (Central France and Central part of the United Kingdom) in the 2000 created scenarios. The full load hours of wind as well as solar technologies differ between the years and are normally distributed. However, the variance is significantly larger for wind than for solar generation.[10]

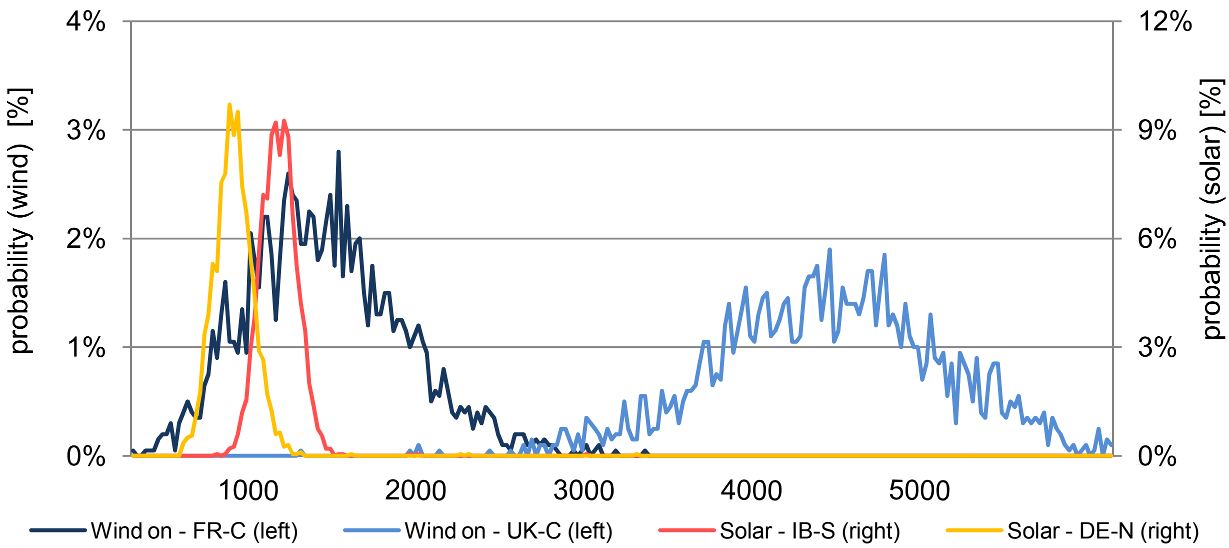

Figure 1: Distribution of full load hours in two wind and two solar regions in the 2000 scenarios

3.2.2. Heuristic to select representative feed-in structures

Due to computational constraints not all 2000 created feed-in structures can be used as input data in the stochastic electricity market model. Therefore, representative feed-in structures are selected which are

[10] As the estimation of yearly full load hours is based on resampling 30 instead of 365 days, it is possible that the variance of full load hours is overestimated. To account for a possible overestimation, we exclude the 10 % quantil on each side.

supposed to consider the characteristics of wind and solar feed-in availability throughout Europe. For this purpose, we define an indicating value for the yearly availability of wind power and an indicating value for the yearly availability of solar power in Europe.

The importance of a specific wind or solar site for an electricity system is mainly defined by the area potential and the expected power generation (full load hours). Therefore, we define the indicating values as the average availability of the most important wind (solar) sites in Europe in terms of these two factors. For wind power, we calculate the average full load hours of onshore wind in the Northern part of the United Kingdom, Germany, the Iberian Peninsula and Poland and wind sites at the atlantic coast of France as well as offshore wind at Norway's coastline. For solar power, we select the Southern part of Italy, the Iberian Peninsula, France and Germany. From the distribution of the indicating values, we pick ten feed-in structures with the following characteristics: S1 extremly low wind year; S2 low wind year; S3 average wind year; S4 high wind year; S5 extremly high wind year; S6 extremely low solar year; S7 low solar year; S8 average solar year; S9 high solar year; S10 extremly high solar year. Table 12 shows the full load hours in the selected scenarios. Apart from the yearly amount of electricity generation the selected feed-in structures consider different hourly correlations between regions and between technologies (wind and PV).

The bounds (lowest and highest full load hours) for each category are chosen such that the probability for the extreme scenarios amounts to 2.5 %, for the low and high scenario to 10 % and the average scenario to 25 %. As the probablility for an extremely high wind year is lower than an average wind year, the different dispatches in the stochastic optimization model are weighted by the specific probability factor as also shown in Table 12.

Table 12: Full load hours of wind and solar technologies in the selected scenarios [h]

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
			wind					solar		
	- -	-	+/-	+	++	- -	-	+/-	+	++
Indicating value "wind"	**3,162**	**3,350**	**3,530**	**3,651**	**3,998**	**3,344**	**3,026**	**3,345**	**3,501**	**3,697**
Indicating value "solar"	**1,103**	**1,180**	**1,159**	**1,162**	**1,037**	**1,010**	**1,053**	**1,174**	**1,234**	**1,285**
Realization probability [%]	**2.5**	**10.0**	**25.0**	**10.0**	**2.5**	**2.5**	**10.0**	**25.0**	**10.0**	**2.5**
Wind onshore										
DE-C	1,694	1,534	1,530	2,146	1,499	1,703	1,696	1,381	1,909	1,656
DE-S	1,657	1,945	1,531	1,848	730	1,244	1,643	1,600	1,789	1,657
DE-N	2,869	2,531	3,122	2,576	3,042	2,838	1,818	2,472	2,226	2,949
LU-N	2,039	2,012	1,941	2,889	2,187	2,084	2,220	2,693	2,995	2,769
LU-S	1,873	1,873	1,773	2,404	2,133	1,953	1,873	1,909	2,305	2,164
IB-C	913	641	618	826	1,139	746	1,274	964	471	873
IB-S	1,932	2,063	1,931	2,273	1,998	1,380	2,278	2,227	1,157	1,545
IB-N	4,245	3,057	3,870	4,258	4,839	3,353	3,841	3,094	3,756	3,384
UK-N	3,554	5,515	4,961	4,820	5,506	3,647	4,149	5,749	4,495	5,006
UK-C	2,843	2,855	3,915	3,126	3,176	3,373	3,251	3,812	3,263	3,030
UK-W	2,839	3,379	3,008	3,790	4,307	3,129	3,003	4,108	3,692	3,555
FR-C	1,998	1,329	748	1,777	1,799	1,264	1,571	1,053	1,588	2,278
FR-S	2,200	2,225	2,603	2,153	2,678	2,093	2,304	2,147	2,226	2,345
FR-W	2,591	2,154	1,547	3,065	3,155	2,462	2,428	2,154	2,400	2,629
CH-C	448	457	565	511	660	382	466	343	340	487
AT-C	1,261	1,804	1,484	1,256	1,404	1,748	1,355	1,297	1,210	1,501
CZ-C	1,444	1,292	1,211	1,015	1,287	1,412	1,634	1,159	1,097	1,452
PL-N	3,269	3,256	3,300	3,039	3,502	3,284	2,673	2,877	2,933	3,585
PL-C	1,321	1,519	1,639	1,234	1,442	1,795	1,744	1,352	1,275	1,492
DK-C	2,620	3,883	4,600	4,416	4,228	3,710	3,010	3,396	3,843	4,528
SK-W	1,563	1,745	1,451	1,527	2,424	1,422	1,938	1,973	2,221	1,881
SK-C	2,323	3,320	3,281	4,144	3,511	2,777	2,350	3,828	3,561	3,094
IT-N	803	557	1,093	1,162	1,111	776	1,832	974	692	656
IT-S	2,816	1,674	2,275	1,960	2,185	1,813	2,259	1,835	1,716	1,566
ET-C	1,237	1,228	1,368	1,066	1,058	1,380	1,642	1,246	1,001	1,311
ET-S	922	1,236	952	706	569	882	1,032	532	941	593
ET-N	2,352	2,754	2,159	3,612	2,639	2,515	2,550	2,934	2,703	3,255
Wind offshore										
DE-N	4,478	4,798	5,964	6,147	4,993	4,703	4,481	4,970	5,573	5,083
LU-N	3,973	4,251	5,613	5,369	5,397	4,488	5,208	5,387	5,742	4,648
IB-W	2,247	2,061	1,976	2,246	2,248	1,633	2,153	2,413	1,146	1,521
UK-W	4,425	5,390	5,100	5,482	5,444	4,731	4,604	5,395	5,385	4,812
FR-W	5,207	5,011	4,333	4,439	6,633	5,380	4,852	5,580	4,850	4,641
PL-N	4,671	4,583	5,198	6,142	5,717	4,809	3,887	4,667	4,048	4,931
DK-N	3,751	5,268	6,818	5,666	5,115	5,147	4,856	5,153	5,584	5,311
SK-W	3,160	5,720	6,336	5,180	5,143	4,998	4,395	5,363	5,997	6,077
IT-W	4,620	4,811	4,920	4,579	3,824	4,722	4,518	5,442	4,763	4,293
ET-N	4,671	4,583	5,198	6,142	5,717	4,809	3,887	4,667	4,048	4,931
Solar power										
DE-C	823	744	805	842	703	720	742	890	843	905
DE-N	820	783	785	748	658	667	654	849	812	915
DE-S	870	903	917	823	747	766	881	938	932	1,024
LU-C	904	731	708	721	666	602	734	729	750	838
IB-C	1,126	1,257	1,202	1,324	1,153	1,168	987	1,281	1,268	1,297
IB-N	982	1,072	939	1,137	859	922	954	1,138	1,124	1,109
IB-S	1,337	1,436	1,306	1,505	1,284	1,246	1,270	1,442	1,439	1,540
UK-C	833	834	823	792	680	677	762	876	750	924
FR-C	975	936	927	735	799	658	870	928	944	1,012
FR-S	921	871	877	932	746	854	883	1,073	961	1,141
FR-W	1,020	1,076	1,162	1,197	1,041	1,004	1,006	1,185	1,239	1,343
CH-C	972	910	875	777	752	767	883	917	932	1,079
AT-C	889	996	840	779	649	746	831	833	925	1,105
CZ–C	665	764	868	868	741	680	685	838	847	890
PL-C	713	932	911	962	843	860	669	917	1,023	1,000
DK-C	921	857	807	809	642	619	725	887	764	958
SK-C	824	885	812	789	681	628	715	762	775	908
IT-C	1,183	1,306	1,252	1,124	1,075	1,023	1,056	1,132	1,326	1,232
IT-N	973	1,127	1,087	1,038	878	920	929	1,069	1,142	1,294
IT-S	1,294	1,320	1,067	1,323	1,166	1,185	1,055	1,391	1,416	1,282
ET-C	930	1,092	1,043	978	934	950	774	931	1,178	1,104
ET-N	733	759	798	780	686	706	730	705	703	828
ET-S	1,100	1,314	1,033	1,280	1,117	1,094	970	1,287	1,096	1,297

4. Optimization of the European electricity mix for different levels of RES-E

We develop a two stage stochastic investment and dispatch model to determine the cost-minimal electricity mix and dispatch considering the uncertain feed-in structures of wind and solar technologies in 59 regions for a political target year e.g. 2050. One can interpret the first stage as the timeframe before 2050 where investments can be made and the second stage as the usage of these technologies to supply the electricity demand in the target year. By using a stochastic model the investment decision has to be made under uncertainty about the local feed-in structure, the amount of yearly generated electricity of wind and solar technologies and the correlation between regions and technologies.[11] In this section, the electricity market model (4.1) is described and an overview of the model assumptions (4.2) is given. In subsection 4.3, the results of the stochastic model are discussed and compared to the deterministic results.

4.1. Model description

The model includes possible investments in conventional, renewable and short as well as long term storage technologies in Europe. The realized dispatch respects technical constraints e.g. ramp-up restrictions, renewable curtailment and transmission limits between regions based on net transfer capacities. The model sets, parameters and variables are shown in Table 13.

4.1.1. Key model elements

The model has to assure that electricity supply meets the hourly demand in all modeled countries for each feed-in structure of wind and solar technologies.[12] Demand can be met by electricity generation in power plants within the country or by imports from other countries. Apart from the physical power supply the model has to build enough securely available capacity to assure electricity supply at peak demand.

$$\sum_a \left[G(a,c,h,s) \cdot \eta(a) \right] + \sum_e \left[I(c,e,h,s) \cdot \left(1 - \delta(c,e) \cdot \beta \right) - E(c,e,h,s) \right] - \sum_{st} \left[S(st,c,h,s) \right] = \rho(a,c,h) \quad (4)$$

$$\sum_a \left[C(c,a) \cdot \tau(a) \right] \geq \theta \quad (5)$$

[11] For clarification, we assume perfect foresight within each dispatch realization as such short term uncertainties e.g. short noticed power plant outages of forecast errors for fluctuating RES-E generation are not modeled and therefore system costs are higher in reality. However, the underestimation occurs in the deterministic as well as in the stochastic model and it can be assumed that is has a similar impact in both models.

[12] As typical in stochastic models the uncertainty is reflected by modeling different scenarios weighted by their specific probability.

Table 13: Model abbreviations including sets, parameters and variables

Abbreviation	Dimension	Description
Model sets		
a		Technologies
c (alias: e)		Regions
h		Hours
res		Renewable energies
s		Scenarios
st	Subset of a	Storage technologies
Model parameters		
annuity	€$_{2010}$/MW	Technology specific investment costs (annuity)
attc	€$_{2010}$/MWh$_{th}$	Attrition costs for ramp-up operation
avail	%	Availability of generation units
facCO	t CO_2 /MWh$_{th}$	CO_2 emissions per fuel consumption
fomc	€$_{2010}$/MW	Fixed operation and maintenance costs
fuelpr	€$_{2010}$/MWh$_{th}$	Fuel price
hpr	€$_{2010}$/MWh$_{th}$	Remuneration per generated heat unit
htp	MWh$_{th}$/MWh$_{el}$	Heat-to-power ratio
prCO	€$_{2010}$/t CO_2	Costs for CO_2 emissions
prob	%	Scenario probability
β	MW/km	Average transmission loss per kilometer
δ	km	Distance between two regions
κ	%	Own consumption of thermal power plants
η	%	Net efficiency
ρ	MW	Model demand
θ	MW	Peak demand
τ	%	Factor for securely available capacity
ψ	%	Conversion efficiency for heat generation
ω	%	RES-E quota on gross electricity demand
Model variables		
C	MW	Installed capacity (net)
CUP	MW	Ramping capacity (net)
E	MW	Exports
G	MWh$_{el}$	Electricity generation (net)
I	MW	Imports
S	MWh	Consumption in storage operation
TCOST	€$_{2010}$	Total system costs

The objective of the model is to minimize total system costs, which are defined by investment, fixed operation and maintenance costs, variable costs including fuel as well as CO_2 and costs due to ramping thermal power plants. The investment and fixed operation and maintenance costs depend on the chosen capacities in the first stage decision. Due to the model approach we use annualized investment costs which include financial costs.[13] The fixed operation and maintenance costs represent staff costs, insurance charges and fix maintenance costs. The variable system costs for electricity generation depend on the cost-minimized dispatch of conventional, renewable and storage technologies for the different feed-in structures of fluctuating

[13]The depreciation time is assumed to be the technical lifetime for all technologies (10 percent interest rate).

renewable energies. Variable costs are determined by fuel prices, CO_2 emission-factors, CO_2 price, net efficiencies and the generation of all technologies weighted by the scenario probability. Modeling ramp-up restrictions and ramping costs of thermal power plants is difficult in linear optimization models. To actually account for technical restrictions, a mixed-integer optimization model is needed which increases the computational time significantly. We simulate ramp-up costs by referring to the power plant blocks and by setting a minimal load restriction similar as described in Richter (2011). Depending on the minimum load and start-up time of thermal power plants, additional costs for ramping occur (attrition and extra fuel costs).

$$
\begin{aligned}
minimize\; TCOST = \sum_{c,a} \left[C(c,a) \cdot \left[annuity(a) + fomc(a) \right] \right] \\
+ \sum_{c,a,h,s} \left[prob(s) \cdot G(c,a,h,s) \cdot \left[\frac{fuelpr(a) + facCO(a) \cdot prCO)}{\eta(a)} \right] \right] \\
+ \sum_{c,a,h,s} \left[prob(s) \cdot CUP(c,a,h,s) \cdot \left[\frac{fuelpr(a) + facCO(a) \cdot prCO + attc(a)}{\eta(a)} \right] \right] \\
- \sum_{c,a,h,s} \left[prob(s) \cdot G(c,a,h,s) \cdot \left[\frac{htp(a) \cdot hpr}{\psi} \right] \right]
\end{aligned} \tag{6}
$$

Apart from the basic cost equations, the model incorporates all common elements of linear dispatch models such as storage restrictions, net transfer possibilities and restrictions for combined heat and power (CHP) generation. The possibility for combined heat and power generation is simulated by a maximum potential for heat generation in CHP power plants specific to each region and the inflexibility of CHP power plants is represented by longer ramp-up times. The generated heat is remunerated by the assumed gas price (divided by the conversion efficiency of the assumed reference heat boiler - 90 %) which roughly represents the opportunity costs for households and industries. The availability of conventional, nuclear, dispatchable renewable energies and storage capacities is reduced by possible outages (planned or not planned).

4.1.2. Modeling stochastic feed-in structures of renewable energies

The model includes the following renewable energy technologies: PV (roof and ground), wind (on- and offshore), biomass (solid and gas), biomass CHP (solid and gas), geothermal and hydro (storage and run-of-river) technologies. Biomass, geothermal and hydro technologies are modeled as dispatchable renewables. The availability of fluctuating renewable energies (wind and solar technologies) highly depends on the different scenarios and hours within the scenario. The availability parameter represents the (maximal possible) feed-in of wind and solar plants. This allows the possibility of wind and solar curtailment when not needed due to low demand and full storages or when total system costs can be reduced due to lower ramping costs of thermal power plants.[14] For wind and solar technologies, an available area potential per region is assumed and biomass fuels are restricted (assumptions in subsection 4.2). The generation of renewable energies has to at least equal on average (average of all modeled scenarios) a pre-defined European RES-E quota on the gross electricity demand. Gross electricity demand includes net electricity demand, storage consumption, own consumption of thermal power plants and transmission losses.[15]

$$G(c,a,h,s) \leq avail(c,a,h,s) \cdot C(c,a) \tag{7}$$

$$\sum_{c,res,h,s} G(c,res,h,s) \geq \omega \cdot \left[\sum_{c,a,h,s} \left[\rho(c,h,s) + S(c,st,h,s) + G(c,a,h,s) \cdot \frac{1}{(1-\kappa(a))} \right] + \sum_{c,e,h,s} \left[E(c,e,h,s) \cdot \delta(c,e) \cdot \beta \right] \right] \tag{8}$$

Using a stochastic model, scenarios with lower or stronger wind or solar years as well as worse or better fitting feed-in structures in terms of meeting demand are incorporated. Therefore the model results are robust solutions for the cost-minimal electricity mix considering different feed-in structures of renewable energies.

4.2. Assumptions

In this section, the technical and political assumptions for the target year 2050 are described. Apart from the assumed net electricity demand, potential heat generation in CHP power plants, the European transmission grid (net transfer capacities), economic and technical parameters for generation units, fuel and CO_2 prices are presented. The assumptions are based on several databases such as ENTSO-E (2011a), IEA (2010), Prognos/EWI/GWS (2010), DLR/IWES/IFNE (2010), Pehnt and Höpfner (2009), Pieper and Rubel (2010), EWI (2010) and EEA (2009).

[14] Wind sites are usually larger than solar sites and therefore transaction costs for solar curtailment are assumed to be higher than for wind sites. We used low variable costs for offshore wind and even lower ones for onshore wind sites. Therefore the model chooses offshore wind curtailment first.

[15] Due to the constraint of an average electricity generation by renewable energies of all modeled scenarios, it is not obvious how to apply decompositon methods such as Benders Decomposition (Benders, 1962) to divide the optimization problem into a master (investment) and subproblems (dispatch). Therefore only a limited amount of scenarios can be considered in the extended version of this model.

4.2.1. Electricity demand and potential for heat in co-generation

Table 14 shows the assumed net electricity demand of the modeled European countries in the target year 2050. The net electricity demand is assumed to decrease in all European regions by 25 percent until 2050. The demand structure is assumed to be similar as today (ENTSO-E, 2011a).

Table 14: Assumed net electricity demand in 2008 and 2050 [TWh]

	AT	LU	CH	CZ	DE	DK	ET	FR	IB	IT	PL	UK	SK
2008	57.3	194.7	57.5	57.6	528.8	35.6	159.0	421.8	293.7	300.7	115.4	365.2	321.1
2050	47.7	158.5	47.7	49.7	440.6	29.3	145.5	360.0	243.1	250.0	104.0	308.3	267.6

The heat potential for combined heat and power generation is assumed to be the same as today. For Germany this means a total potential of 191 TWh_{th} (Italy 177 TWh_{th}; Benelux 132 TWh_{th} and Poland 97 TWh_{th}). The generated heat is remunerated by the assumed gas price (divided by the conversion efficiency of the assumed reference heat boiler - 90 %) which roughly represents the opportunity costs for households and industries.

4.2.2. Net transfer capacities

In our model simulation, net transfer capacities between European regions are assumed to be expanded by 20 % compared to today (today's capacities based on ENTSO-E (2011b)). Table 15 shows the assumed NTC values between the modeled European regions.

Table 15: Assumed net transfer capacities in 2050 [MW]

	AT	LU	CH	CZ	DE	DK	ET	FR	IB	IT	PL	UK	SK
AT	-	-	1,200	960	1,920	-	1,440	-	-	84	-	-	-
LU	-	-	-	-	4,620	-	-	3,480	-	-	-	-	840
CH	648	-	-	-	1,800	-	-	3,600	-	1,728	-	-	-
CZ	720	-	-	-	960	-	1,200	-	-	-	2,400	-	-
DE	1,920	3,600	3,840	2,520	-	2,460	-	3,120	-	-	1,320	-	720
DK	-	-	-	-	1,680	-	-	-	-	-	-	-	3,516
ET	1,560	-	-	2,040	-	-	-	-	-	144	720	-	420
FR	-	1,560	1,320	-	3,660	-	-	-	600	1,044	-	2,400	-
IB	-	-	-	-	-	-	-	1,440	-	-	-	-	-
IT	240	-	4,152	-	-	-	396	2,880	-	-	-	-	-
PL	-	-	-	960	960	-	600	-	-	-	-	-	-
UK	-	-	-	-	-	-	-	2,400	-	-	-	-	-
SK	-	840	-	-	720	4,068	420	-	-	-	-	-	-

4.2.3. Technical and economic parameters for generation technologies

The model includes conventional (potentially equipped with CCS or combined heat generation), nuclear, renewable and storage technologies. Table 16 shows the assumed technical as well as cost related parameters for the available technologies. Compared to today, investment costs (€$_{2010}$) especially for renewables are assumed to decrease until 2050. The assumptions are based on different databases such as IEA (2010), Prognos/EWI/GWS (2010) and DLR/IWES/IFNE (2010).

Table 16: Technical and economic parameters for generation technologies in 2050

Technology	Investment costs [€$_{2010}$/kW]	FOM costs [€$_{2010}$/kWa]	Lifetime [a]	η (η_{load}) [%]	Heat-to-power [MWh$_{th}$/MWh$_{el}$]
Lignite	1,950	43	45	46.5	-
Coal	1,650	36	45	50.0	-
Nuclear	3,160	97	60	33.0	-
CCGT	950	28	30	60.0	-
OCGT	400	17	25	40.0	-
Lignite-CCS	2,450	103	45	37.0	-
Coal-CCS	1,850	97	45	40.5	-
CCGT-CCS	1,088	88	30	52.0	-
Lignite CHP	2,600	70	45	22.5	3.0
Coal CHP	2,050	55	45	22.5	3.0
Gas CHP	1,500	40	30	36.0	1.5
Pump-Storage	2,300	12	100	87.0 (83.0)	-
Hydro-Storage	2,300	12	100	87.0	-
CAES-Storage	850	10	30	86.0 (81.0)	-
Hydrogen-Storage	3,500	10	20	45.0 (65.0)	-
Wind onshore	1,100	41	25	-	-
Wind offshore (shallow)	2,400	136	25	-	-
Wind offshore (deep)	2,800	160	25	-	-
PV base	1,080	30	25	-	-
PV roof	1,260	35	25	-	-
Geothermal	9,050	300	30	-	2.0
Hydro river	4,500	50	100	-	-
Biomass-solid	3,300	165	30	30.0	-
Biomass-gas	2,400	120	30	40.0	-
Biomass-solid CHP	3,500	165	30	22.5	3.0
Biomass-gas CHP	2,600	120	30	22.5	1.5

As storage technologies are an important option to balance the stochastic feed-in of renewables and demand, we model short and long term storage technologies. Hydrogen-storage units are an already existing option but investment costs are higher compared to other storage technologies. The advantage of hydrogen-storage technologies include larger storage volumes and therefore the availability to overcome periods with low feed-in of fluctuating renewables (Pehnt and Höpfner, 2009; Pieper and Rubel, 2010).

4.2.4. Fuel and CO_2 prices

Table 17 shows the assumed fuel and CO_2 prices for 2050. The prices for fossil fuels are assumed to be similar as in the high price year 2008. As we model several biomass technologies a range for fuel prices is given. Due to a high demand for biomass fuels in the scenarios, the prices for biomass solid are assumed to slightly increase from 21.2 to 22.4 €$_{2010}$/MWh$_{th}$ (similar development as assumed in EWI (2010)). As a political target year is modeled a relatively high price of 40.0 €$_{2010}$/tCO_2 for CO_2 emissions is assumed.

Table 17: Fuel and CO_2 prices

		2008	2050
Nuclear	[€$_{2010}$/MWh$_{th}$]	3.6	3.3
Lignite	[€$_{2010}$/MWh$_{th}$]	1.4	1.4
Hard coal	[€$_{2010}$/MWh$_{th}$]	17.3	14.7
Gas	[€$_{2010}$/MWh$_{th}$]	25.2	30.0
Biomass solid	[€$_{2010}$/MWh$_{th}$]	15.0-21.2	15.0-22.4
Biomass gas	[€$_{2010}$/MWh$_{th}$]	0.1-50.0	0.1-60.0
CO_2 price	[€$_{2010}$/tCO_2]	22.0	40.0

4.2.5. Fuel potential for lignite and biomass as well as area potential for storage and RES-E technologies

Lignite and biomass fuels, the possibilities for large storage sites as well as the land for wind and solar sites is limited. The potential for biomass fuels is bordered due to land restrictions and competition with alternative utilizations such as for food production. For the example of France, a fuel potential of 283 TWh$_{th}$ for biomass solid and 72 TWh$_{th}$ for biomass gas is assumed. Due to an assumed increasing demand for liquid biomass fuels in the mobility sector, these fuels are not available to the electricity sector. The potential of hydro technologies (pump-storage, hydro-storage and run-of-river) is restricted to the already existing sites. The available land for photovoltaics and wind turbines is mainly determined by political decisions regarding the importance of the deployment of renewable energies and the overall social acceptance. As we model a political target the assumptions about the available land for RES-E sites are rather optimistic. The potential for offshore wind sites is especially difficult to determine because of limited experience with large offshore wind sites. Table 18 shows the assumed available area for wind turbines in the distinguished regions in Europe (similar to EEA (2009) and EWI (2010)).

Table 18: Available land area for wind sites in km^2

	AT	LU	CH	CZ	DE	DK	ET	FR	IB	IT	PL	UK	SK
Onshore	199	497	53	485	2,174	300	1,252	3,215	1,810	578	1,944	2,442	870
Offshore	-	11,054	-	-	7,200	8,520	5,640	4,050	1,960	2,680	1,410	17,340	19,790

4.3. Model results

4.3.1. Cost minimal electricity mix depending on the modeled RES-E quota (stochastic model)

The optimal generation capacities and annualized total system costs for Europe depend on the prescribed RES-E generation quota as shown in Figure 2.[16] Due to the lower availability of fluctuating RES-E capacities compared to conventional power plants, the total capacity increases when modeling high RES-E scenarios. Due to the negative correlated feed-in structures, a mix of wind and solar technologies is cost-efficient from a system point of view even though additional wind capacities with lower average generation costs are available when modeling a high RES-E share. Due to the limited potential for low cost renewable options and the integration costs for renewables such as additional costs for back-up capacities, total system costs increase significantly when modeling high RES-E quotas (greater than 60-70 %).

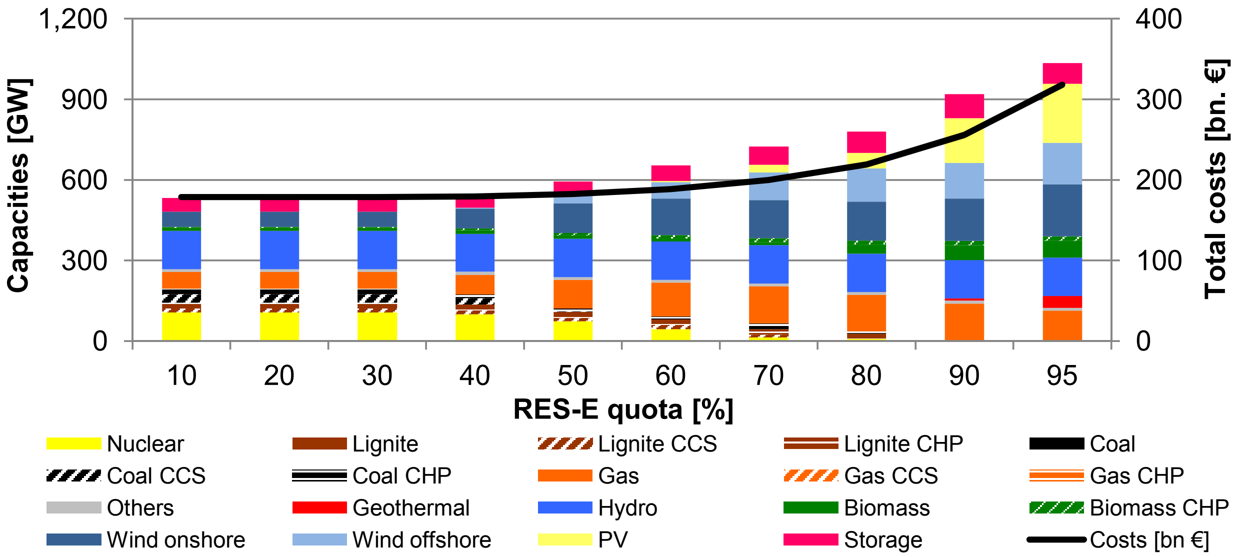

Figure 2: Optimal capacities and yearly system costs considering the uncertain availabiliy of wind and solar power in Europe

No RES-E quota leads to about 35 % generation by renewable energies (hydro 57 %; wind 24 %; biomass 12 % and others 7 %) which are cost-efficient given the assumed investment and fuel costs. Baseload generation takes place in nuclear as well as lignite fired power plants equipped with CCS-technology, mid load is generated in coal capacities and the balancing of wind generation and demand is mainly realized by gas fired power plants. A higher RES-E quota (until 60 %) leads to higher investments in onshore wind turbines especially in in the United Kingdom and France; offshore wind mainly in Germany, France and Italy; and short term storage capacities in the United Kingdom. The storage capacities help to overcome

[16]Total system costs represent annualized investment costs, yearly fixed operation and maintenance costs, variable costs incl. ramping costs of thermal power plants and the remuneration for generated heat in CHP plants.

short periods with lower wind or solar generation. For conventional power plants, less investments take place in coal (Germany and Italy) and nuclear power (United Kingdom and France) but more flexible gas capacities are build (especially in Germany, United Kingdom and Italy). A higher RES-E quota of up to 80 % brings out a mix of photovoltaics in Italy, the Iberian Peninsula and Southern France; more wind on- and offshore capacities in Germany, the United Kingdom, and Poland; and high cost biomass capacities in France and the Iberian Peninsula. To integrate the fluctuating renewables more storage capacities are installed mainly in Germany, France and Poland. Almost no baseload capacities such as nuclear, lignite and coal capacities equipped with CCS are installed. An even higher RES-E quota also leads to significantly higher investments in onshore wind capacities at less favorable sites, biomass capacities and geothermal sites. Also, more investments in photovoltaics - especially on the Iberian Peninsula, Italy and Germany - are cost-efficient even though more wind sites with lower levelized costs are available within these countries.

The annual total system costs for the European electricity system highly depend on the implied RES-E quota. When no RES-E quota is modeled, the yearly system costs amount to 178.7 bn. €$_{2010}$. Due to the conventional power dominated generation mix, variable costs make up almost 30 % of the total system costs. A higher demanded RES-E quota of up to 60 % leads to only a small increase of the total costs to 188.5 bn. €$_{2010}$. Due to the transformation to a primarily renewable based generation mix, total system costs are then dominated by investment and fixed operation and maintanance costs which make up almost 90 %. Considering the model assumptions a higher RES-E quota leads to a significant increase of total costs (219.2 bn. €$_{2010}$ for 80 % RES-E and 255.8 bn. €$_{2010}$ for 90 % RES-E) due to the limited potential of low cost RES-E options and high integration costs of fluctuating RES-E generation.

The generation (utilization rate) by technologies highly depends on the availability of fluctuating RES-E generation and therefore on the specific year (scenario). Large wind and photovoltaic capacities lead to a more fluctuating generation structure and a more volatile yearly generation (absolute figures). Due to the marginal generation costs, fluctuating RES-E technologies are used when available and when an integration into the electricity grid is possible. Figure 3 shows the maximal, minimal and average yearly generation by fuels for the different feed-in structures of wind and solar technologies when implying a 60 % (left side) and a 80 % (right side) RES-E quota.[17]

[17] The maximal and minimal generation by wind turbines and photovoltaics are extreme values which only occur by a probability of 2.5 %. However, the electricity system also needs to be able to meet demand cost-efficiently in these extreme years.

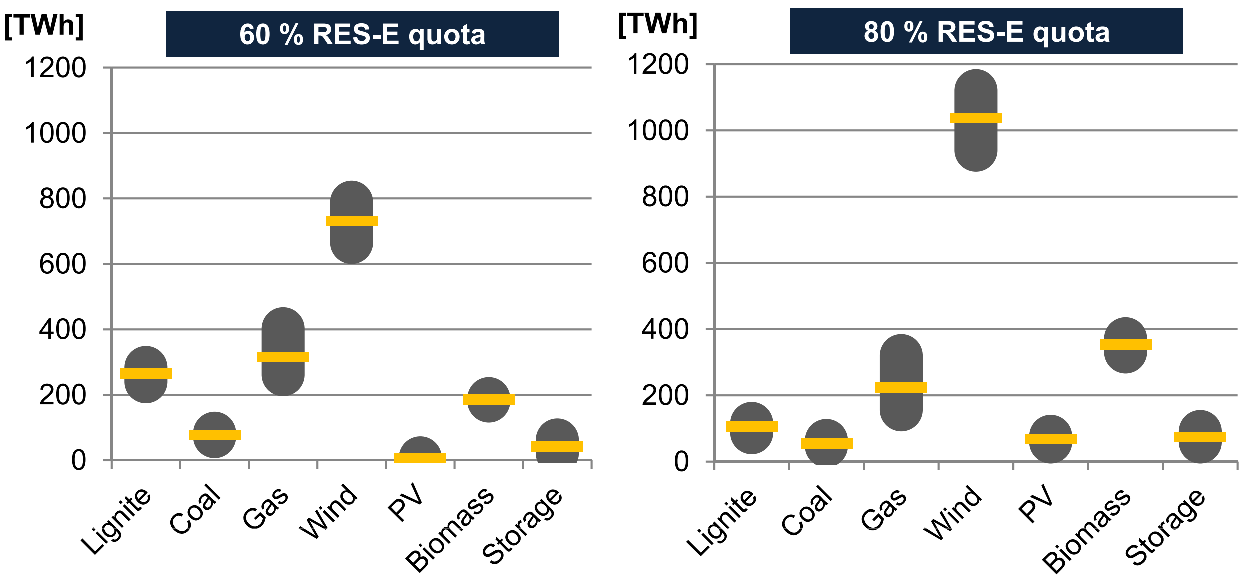

Figure 3: Range of generation by fuels depending on the availability of wind and solar generation [TWh]

Figure 3 reflects that the generation of conventional technologies depends sensitively on the specific feed-in of wind and solar technologies: When a 60 % RES-E quota has to be reached lignite capacities generate on average 265 TWh (6,700 full load hours); coal capacities 77 TWh (6,000 full load hours) and gas fired power plants 316 TWh (2,100 full load hours). However, depending on the availability of wind and solar generation the realized full load hours of conventional power plants vary significantly between years (scenarios). Due to relatively low investment costs, gas fired power plants are used as back-up capacities to balance the stochastic wind and solar generation. In a high wind and solar year (scenario), gas fired power plants only generate about 262 TWh (lower than 2,100 full load hours) but are highly used with almost 402 TWh (3,300 full load hours) in a low wind and solar year. A higher RES-E quota leads to an electricty system which is primarily based on fluctuating RES-E capacities and the differences in the utilization rates of the conventional power plants are even greater among the scenarios.

4.3.2. The influence of stochastic full load hours and uncertain correlations between regions and technologies

The above discussed results of the stochastic optimization model are compared to deterministic model results to quantify the deviation with regard to the cost-efficient capacity mix and total system costs depending on the share of RES-E generation when neglecting the stochastic availability of wind and solar plants. We use the feed-in structures of wind (on- and offshore) and solar sites of the average wind scenario (scenario 3) as input data in the deterministic model. The feed-in structures represent average yearly full load hours as well as average correlations between regions and technologies. Figure 4 shows the optimal capacities as well as total system costs when modeling deterministic full load hours and correlations (left side) and in comparison to the stochastic model results (right side; + means higher values in the stochastic model). In general, a similar development of capacities can be seen as when considering the uncertainty about the availability of wind and solar power. However, the results show that the value of fluctuating renewable technologies are overestimated and total system costs underestimated when neglecting the stochastic availability of these technologies by applying deterministic investment and dispatch models. Furthermore, the value of solar technologies - relative to wind turbines - is underestimated when neglecting the negative correlation between wind speed and solar radiation.

In the stochastic model, when no RES-E quota has to be reached more baseload capacities, specifically nuclear and coal, are built instead of wind turbines. As the value of wind turbines is lower due to the uncertain yearly availability, less on- and offshore wind capacities at relatively low costs sites in the United Kingdom and Norway are installed. When modeling RES-E quotas of 40-50 % less coal plants equipped with CCS are installed and mainly replaced by more flexible as well as less capital intensive gas fired power plants. Higher RES-E quotas than 60 % are reached with more onshore wind capacities mainly in Germany and the Iberian Peninsula; solar plants in Italy, Germany and the United Kingdom; and biomass as well as geothermal capacities. More wind and solar capacities are needed for two reasons: First, as better or worse wind and solar years are considered more capacities are needed to ensure the achievement of the RES-E target. Second, as uncertainty about the regional availability and uncertainty about the correlation between regions and technologies are considered the capacity mix cannot be optimized for one specific year.

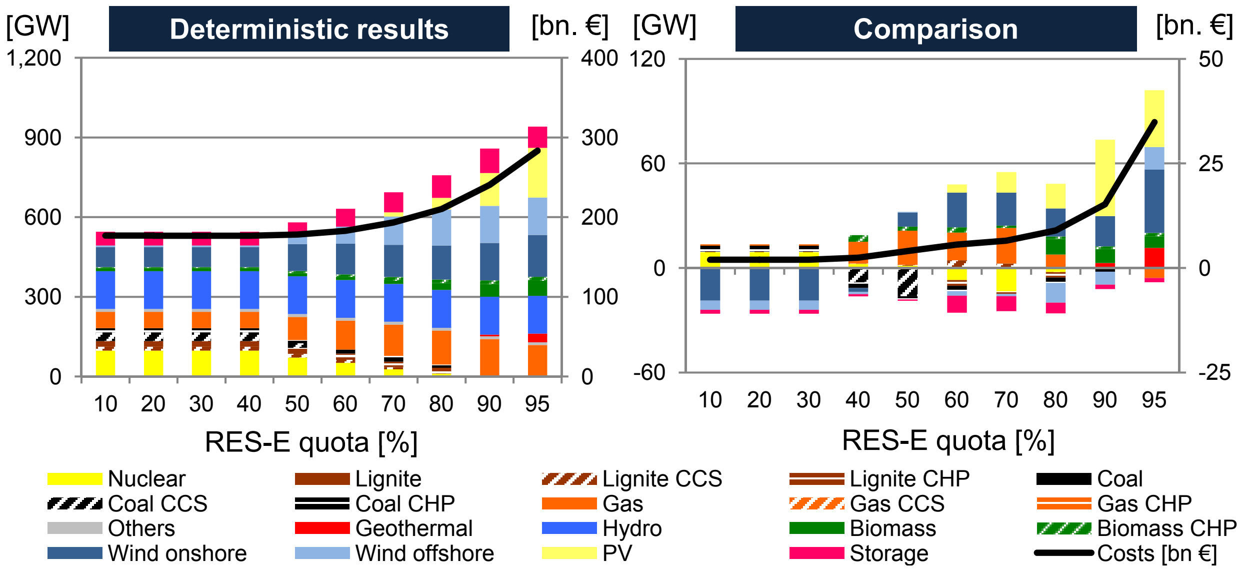

Figure 4: Comparison of stochastic to deterministic model results

Total system costs are higher in the stochastic model due to the uncertainty about the availability of wind and solar power. In the stochastic model the power plant mix is optimized under consideration of different wind and solar availabilities. Therefore the power plant fleet is a robust solution for the long term power plant mix but not optimal in each specific year. When neglecting the stochastic availability of wind and solar power, the capacity mix and utilization can be optimized for an average wind and solar year. Hence, total system costs are lower when modeling deterministic full load hours as well as correlations. Table 19 shows the total costs in billion €$_{2010}$ for the stochastic and deterministic model as well as the comparison in absolute and relative values (as percentage of the deterministic solution).

In case of a 50 % RES-E quota, yearly total costs of the modeled electricity system amount to 178.2 bn. €$_{2010}$ compared to 182.3 bn. €$_{2010}$ in the stochastic model. The cost difference of 4.0 bn. €$_{2010}$ represents about 2.3 % of the deterministic model result. Until a RES-E quota of up to 70 % total system costs as well as the difference between the two models increase linearly. As fluctuating renewables play a more important role in high RES-E electricity systems and the impact of the uncertain availability becomes more significant, the cost difference increases by higher RES-E quotas. For a 95 % RES-E share, the cost difference between the stochastic compared to the deterministic model amounts to 35.5 bn. €$_{2010}$ which represents about 12.5 % of the total system costs.

Table 19: Comparison of total system costs depending on the RES-E quota [bn. €$_{2010}$]

	40%	50%	60%	70%	80%	90%	95%
Stochastic model [bn. €$_{2010}$]	179.2	182.3	188.5	199.8	219.3	255.8	318.2
Deterministic model [bn. €$_{2010}$]	176.8	178.2	182.9	193.2	210.3	240.4	282.8
Difference							
- absolut [bn. €$_{2010}$]	2.5	4.0	5.6	6.6	8.9	15.4	35.5
- percent of det. model [%]	1.4	2.3	3.1	3.4	4.2	6.4	12.5

Based on the simulation results, it is likely that total system costs for high RES-E systems are significantly higher than estimated in many studies. This applies especially for decentralized electricity power systems with a limited grid infrastructure because the balance of fluctuating renewables and demand becomes more difficult. When estimating additional costs for high RES-E systems compared to mainly conventional generation, one has to consider the uncertain availability of wind and solar power. The analysis shows that the additional costs are higher than estimated in deterministic models and that the difference inceases significantly when implying RES-E quotas of more than 70-80 %.

5. Conclusion

We have shown that the stochastic feed-in and different cost structures of wind and solar technologies compared to conventional power plants lead to different requirements for the determination of the optimal electricity mix development. In this paper, an approach is presented to incorporate the stochastic feed-in of renewable energies in an investment and dispatch optimization model for electricity markets and applied to the European electricity system. The simulation results show that fluctuating renewables are significantly overvalued and hence dispatchable renewable energies such as biomass or geothermal sites - even considering high investment or fuel costs - are underestimated in deterministic electricity market models. Furthermore, solar technologies are - relative to wind turbines - underestimated when neglecting the negative correlation between wind speed and solar radiation. The simulation also shows that total system costs are significantly underestimated and this effect increases the higher the RES-E share. Hence, the simulation indicates that total system costs of a primarily renewable based European electricity system will be significantly higher than estimated in many studies.

The analysis approach could be improved and extended in several ways. It would be desirable to also include short term uncertainties such as wind and solar power forecast errors or power plant outages by using continous planning techniques. As already shown in Sun et al. (2008), ignoring short term uncertainties significantly undervalues the needed operational flexibility and can even result in insufficient investments. It would then be interesting to analyze the cost-efficient European pathway to a primarily renewable electricity system considering the stochastic feed-in of fluctuating renewables. The impact of the stochastic availability of wind and solar technologies and the appropriate consideration in long term electricity market models provide interesting areas of further research.

References

Beenstock, M., 1995. The stochastic economics of windpower. Energy Economics 17, 22–37.

Benders, J., 1962. Partitioning procedures for solving mixed-variables programming problems. Numerische Mathematik 4, 238–252.

Dantzig, B., 1955. Linear programming under uncertainty. Management Science 1, 197–206.

DeCarolis, J., Keith, D., 2006. The economics of large scale wind power in a carbon constrained world. Energy Policy 34, 395–410.

DLR/IWES/IFNE, 2010. Langfristszenarien und Strategien für den Ausbau der erneuerbaren Energien in Deutschland bei Berücksichtigung der Entwicklung in Europa und global. Tech. rep., Nitsch, J., Pregger, T., Scholz, Y., and Naegler, T. (Deutsches Zentrum für Luft- und Raumfahrt - DLR) Sterner, M., Gerhardt, N., von Oehsen, A., Pape, C., and Saint-Drenan, Y. (Fraunhofer Institut für Windenergie und Energiesystemtechnik - IWES) and Wenzel, B. (Ingenieurbüro für neue Energien - IFNE).

EEA, 2009. Europe's onshore and offshore wind energy potential - an assessment of environmental and economic constraints. Tech. rep., Coppens, C., Gordijn, H., Piek, M., Ruyssenaars, P., Schrander, J., de Smet, P., Swart, R., Hoogwijk, M., Papalexandrou, M., Visser, E., Horalek, J., Kurfürst, P., Jensen, F., Petersen, B., Harfoot, M., Milego, R., Clausen, N., and Giebel, G. (prepared by the European Environmental Agency).

Efron, B., 1979. Bootstrap methods: Another look at the jackknife. The Annals of Statistics 7, 1–26.

ENTSO-E, 2011a. Yearly electricty consumption data for Europe.
URL `https://www.entsoe.eu/index.php?id=92`

ENTSO-E, 2011b. NTC Matrix for Europe.
URL `https://www.entsoe.eu/resources/ntc-values/ntc-matrix/`

EuroWind, 2011. Database for hourly wind speeds and solar radiation from 2006-2010 (not public). Tech. rep., EuroWind.

EWI, 2010. European RES-E policy analysis - a model based analysis of RES-E deployment and its impact on the conventional power markt. Tech. rep., Fürsch, M., Golling, C., Nicolosi, M., Wissen, R., and Lindenberger, D. (Institute of Energy Economics at the University of Cologne).
URL `http://www.ewi.uni-koeln.de/publikationen/studien/`

EWI, 2011. Roadmap 2050 - a closer look. Cost-efficient RES-E penetration and the role of grid extensions. Tech. rep., Fürsch, M., Hagspiel, S., Jägemann, C., Nagl, S., and Lindenberger, D. (Institute of Energy Economics at the University of Cologne) Glotzbach, L., Tröster, E., and Ackermann, T. (energynautics).
URL `http://www.ewi.uni-koeln.de/publikationen/studien/`

Fripp, M., 2008. Optimal investment in wind and solar power in California. Ph.D. thesis, Energy and Resource Group at the University of California, Berkeley.

Heide, D., Bremen, L., Greiner, M., Hoffmann, C., Speckmann, M., Bofinger, S., 2010. Seasonal optimal mix of wind and solar power in a future, highly renewable Europe. Renewable Energy 35, 2483–2489.

Hsu, S., 1988. Coastal Meterology. Academic Press London.

IEA, 2010. World energy outlook 2010. Tech. rep., International Energy Administration.

Modiano, E., 1987. Derived demand and capacity planning under uncertainty. Operation Research 35, 185–197.

Möst, D., Keles, D., 2010. A survey of stochastic modelling approaches for liberalised electricity markets. European Journal of Operational Research 207, 543–556.

Murphy, F., Sen, S., Soyster, A., 1982. Electric utility capacity expansion planning with uncertain load factors. IIE Transactions 14, 52–59.

Neuhoff, K., Ehrenmann, A., Butler, L., Curst, J., Hoexter, H., Keats, K., Kreczko, A., Sinden, G., 2008. Space and time: Wind in an investment planning model. Energy Economics 30, 1990–2008.

Papaefthymiou, G., Schavemaker, P., van der Sluis, L., Kling, W., Kurowicka, D., Cooke, R., 2006. Integration of stochastic generation in power systems. Electrical Power and Energy Systems 28, 655–667.

Pehnt, M., Höpfner, U., 2009. Wasserstoff- und Stromspeicher in einem Energiesystem mit hohen Anteilen erneuerbarer Energien: Analyse der kurz- und mittelfristigen Perspektive. Tech. rep., Institut für Energie- und Umweltforschung (ifeu).

Pieper, C., Rubel, H., 2010. Electricity storage - making large-scale adoption of wind and solar energies a reality. Tech. rep., The Boston Consulting Group.

Prognos/EWI/GWS, 2010. Energieszenarien für ein Energiekonzept der Bundesregierung. Tech. rep., Schlesinger, M., Hofer, P., Kemmler, A., Kirchner, A. and Strassburg, S. (all Prognos AG); Lindenberger, D., Fürsch, M., Nagl, S., Paulus, M., Richter, J. and Trüby, J. (all EWI); Lutz, C., Khorushun, O., Lehr, U., and Thobe, I (GWS mbH).

Richter, J., 2011. DIMENSION - A dispatch and investment model for European electricity markets (Working Paper No. 11/03) Institute of Energy Economics at the University of Cologne.

Short, W., Blair, N., Heimiller, D., 2003. Wind deployment system (WinDS) model. Tech. rep., National Renewable Energy Laboratory.
URL `http://www.nrel.gov/analysis/`

Sun, N., Ellersdorfer, I., Swider, D., 2008. Model-based long-term electricity generation system planning under uncertainty. In: Int. Conference on Electric Utility Deregualtion and Re-structuring and Power Technologies (DRPT 2008). pp. 1298–1304.

Swider, D., Weber, C., 2006. The costs of wind's intermittency in Germany: application of a stochastic electricity market model. European Transactions on Electrical Power 17, 151–172.

Appendix

5.1. *Appendix A - Abbreviations*

Table 20: Abbreviations

Abbreviation	Description
CAES	Compressed air energy storage
CCS	Carbon capture and storage
CHP	Combined heat and power
RES-E	Renewable energy sources - electricity
PV	Photovoltaic

5.2. *Appendix B - Generation of combined wind and solar feed-in scenarios*

Table 21: Notation of scenario generation parameters

Abbreviation	Dimension	Description
Model sets		
h		Hours
reg		Region
s		Scenario
tech		Technology
Model parameters		
A	m^2	Size solar array
η_{total}	%	Efficiency
normh	m	Turbine height
P_{el}	MW	Power generation
P_{nom}	MW	Nominal capacity
radiation	W/m^2	Solar radiation
refh	m	Height at measurement station
r	m^2	Radius
ρ	kg/m^3	Air density
rough	m	Roughness length
v_{normh}	m/s	Wind speed in turbine height
v	m/s	Wind speed in 30 meters

Table 22: Correlation matrix for modeled wind sites

	DE-C (on)	DE-S (on)	DE-N (on)	LU-N (on)	LU-S (on)	IB-C (on)	IB-S (on)	IB-N (on)	UK-C (on)	UK-S (on)	UK-W (on)	FR-C (on)	FR-S (on)	FR-N (on)	CH-C (on)	AT-C (on)	CZ-C (on)	PL-N (on)	PL-S (on)	DK-C (on)
DE-C (on)	1																			
DE-S (on)	0.651	1																		
DE-N (on)	0.573	0.355	1																	
LU-N (on)	0.610	0.476	0.355	1																
LU-S (on)	0.788	0.563	0.484	0.803	1															
IB-C (on)	-0.020	-0.048	-0.028	0.012	-0.003	1														
IB-S (on)	-0.031	-0.034	-0.039	-0.010	-0.036	0.309	1													
IB-N (on)	0.171	0.116	0.090	0.219	0.209	0.328	0.137	1												
UK-C (on)	0.211	0.164	0.269	0.258	0.256	-0.032	0.004	0.085	1											
UK-S (on)	0.470	0.346	0.330	0.733	0.620	0.005	-0.022	0.163	0.367	1										
UK-W (on)	0.204	0.153	0.159	0.307	0.276	-0.018	-0.026	0.085	0.327	0.353	1									
FR-C (on)	0.437	0.412	0.212	0.527	0.499	0.165	0.120	0.363	0.111	0.340	0.187	1								
FR-S (on)	0.101	0.119	0.068	0.086	0.074	0.179	0.302	0.202	0.044	0.045	0.011	0.220	1							
FR-N (on)	0.234	0.201	0.097	0.296	0.265	0.336	0.220	0.519	0.077	0.202	0.160	0.597	0.260	1						
CH-C (on)	0.269	0.240	0.151	0.209	0.246	0.186	0.116	0.282	0.074	0.161	0.077	0.331	0.320	0.306	1					
AT-C (on)	0.429	0.492	0.377	0.201	0.290	-0.044	-0.027	0.079	0.131	0.169	0.077	0.104	0.150	0.063	0.240	1				
CZ-C (on)	0.554	0.477	0.483	0.251	0.367	0.027	0.022	0.131	0.103	0.173	0.073	0.265	0.220	0.167	0.314	0.588	1			
PL-N (on)	0.289	0.204	0.557	0.151	0.231	-0.055	-0.014	0.029	0.192	0.162	0.143	0.083	0.024	0.054	0.047	0.264	0.323	1		
PL-S (on)	0.344	0.369	0.384	0.173	0.246	-0.025	-0.020	0.059	0.143	0.158	0.097	0.117	0.069	0.075	0.146	0.562	0.491	0.447	1	
DK-C (on)	0.385	0.219	0.646	0.352	0.402	-0.063	-0.060	0.060	0.362	0.378	0.206	0.150	-0.005	0.055	0.091	0.218	0.236	0.414	0.244	1
SK-W (on)	0.122	0.092	0.105	0.154	0.166	0.013	0.054	0.157	0.191	0.143	0.188	0.153	0.036	0.155	0.108	0.059	0.033	0.113	0.081	0.168
SK-S (on)	0.228	0.138	0.414	0.165	0.207	-0.031	0.015	0.061	0.209	0.188	0.134	0.092	0.033	0.082	0.071	0.166	0.181	0.549	0.228	0.386
IT-N (on)	-0.043	0.010	-0.070	-0.027	-0.043	0.091	0.230	0.071	-0.046	-0.030	-0.051	0.059	0.240	0.105	0.048	-0.019	0.050	-0.040	-0.015	-0.090
IT-S (on)	0.055	0.087	-0.003	0.073	0.049	0.165	0.256	0.200	0.039	0.058	0.015	0.164	0.320	0.260	0.275	0.101	0.140	0.014	0.048	-0.049
ET-C (on)	0.268	0.338	0.208	0.128	0.175	0.044	0.052	0.108	0.084	0.102	0.039	0.125	0.153	0.134	0.184	0.509	0.426	0.184	0.553	0.090
ET-N (on)	-0.045	0.003	-0.011	-0.039	-0.044	-0.002	0.080	0.043	0.034	-0.032	0.013	-0.001	0.086	0.031	0.012	0.045	0.028	0.005	0.006	-0.001
ET-S (on)	0.144	0.090	0.205	0.088	0.123	-0.059	0.024	-0.003	0.115	0.096	0.089	0.038	0.003	0.019	0.050	0.085	0.075	0.318	0.161	0.204
DE (off)	0.577	0.329	0.710	0.494	0.596	-0.040	-0.039	0.132	0.333	0.515	0.188	0.235	0.060	0.122	0.176	0.286	0.327	0.354	0.255	0.679
LU (off)	0.562	0.371	0.410	0.779	0.733	-0.035	-0.037	0.182	0.333	0.818	0.308	0.359	0.041	0.193	0.202	0.191	0.204	0.203	0.170	0.443
IB (off)	-0.024	-0.044	-0.029	0.004	-0.018	0.373	0.922	0.193	0.014	-0.003	-0.025	0.141	0.267	0.253	0.141	-0.032	0.015	-0.006	-0.025	-0.046
UK (off)	0.298	0.210	0.244	0.442	0.402	-0.062	-0.053	0.087	0.540	0.601	0.587	0.188	-0.005	0.112	0.095	0.114	0.073	0.178	0.135	0.334
FR (off)	0.222	0.149	0.110	0.404	0.320	0.147	0.059	0.387	0.139	0.372	0.382	0.429	0.057	0.468	0.171	0.035	0.069	0.076	0.056	0.119
PL (off)	0.405	0.246	0.797	0.264	0.363	-0.037	-0.012	0.063	0.257	0.270	0.141	0.148	0.043	0.082	0.090	0.260	0.342	0.659	0.322	0.632
DK (off)	0.407	0.233	0.542	0.451	0.465	-0.046	-0.039	0.119	0.424	0.552	0.236	0.194	0.034	0.096	0.139	0.197	0.212	0.296	0.199	0.763
SK (off)	0.234	0.128	0.346	0.291	0.287	-0.012	-0.017	0.116	0.418	0.335	0.203	0.145	0.030	0.098	0.117	0.123	0.134	0.236	0.119	0.614
IT (off)	0.096	0.141	0.055	0.088	0.074	0.157	0.365	0.164	0.059	0.054	0.027	0.208	0.754	0.249	0.312	0.159	0.177	0.003	0.054	-0.012
ET (off)	0.405	0.246	0.797	0.264	0.363	-0.037	-0.012	0.063	0.257	0.270	0.141	0.148	0.043	0.082	0.090	0.260	0.342	0.659	0.322	0.632

continued

	SK-W (on)	SK-S (on)	IT-N (on)	IT-S (on)	ET-C (on)	ET-N (on)	ET-S (on)	DE (off)	LU (off)	IB (off)	UK (off)	FR (off)	PL (off)	DK (off)	SK (off)	IT (off)	ET (off)
SK-W (on)	1																
SK-S (on)	0.178	1															
IT-N (on)	0.000	-0.033	1														
IT-S (on)	0.063	0.035	0.330	1													
ET-C (on)	0.037	0.074	0.166	0.212	1												
ET-N (on)	0.088	0.025	0.151	0.131	0.115	1											
ET-S (on)	0.131	0.408	0.004	0.012	0.023	-0.004	1										
DE (off)	0.142	0.322	-0.065	0.011	0.131	0.003	0.172	1									
LU (off)	0.179	0.228	-0.060	0.033	0.076	-0.018	0.134	0.660	1								
IB (off)	0.075	0.027	0.200	0.239	0.034	0.066	0.034	-0.019	-0.012	1							
UK (off)	0.204	0.188	-0.085	-0.002	0.037	-0.017	0.135	0.376	0.545	-0.039	1						
FR (off)	0.210	0.103	0.006	0.124	0.052	0.013	0.064	0.180	0.352	0.099	0.337	1					
PL (off)	0.116	0.534	-0.061	-0.001	0.127	0.007	0.233	0.604	0.354	0.003	0.249	0.120	1				
DK (off)	0.157	0.306	-0.070	-0.003	0.078	0.013	0.146	0.773	0.622	-0.019	0.442	0.193	0.502	1			
SK (off)	0.205	0.254	-0.048	0.001	0.042	0.049	0.102	0.450	0.363	0.007	0.320	0.168	0.369	0.641	1		
IT (off)	0.063	0.055	0.255	0.327	0.154	0.109	0.021	0.078	0.068	0.303	0.028	0.084	0.060	0.045	0.043	1	
ET (off)	0.116	0.534	-0.061	-0.001	0.127	0.007	0.233	0.604	0.354	0.003	0.249	0.120	1.000	0.502	0.369	0.060	1

Table 23: Correlation matrix for modeled solar sites - daytime

	DE-C	DE-N	DE-S	LU-C	IB-C	IB-N	IB-S	UK-C	FR-C	FR-N	FR-S	CH-C	AT-C	CZ-C	PL-C
DE-C	1														
DE-N	0.797	1													
DE-S	0.768	0.690	1												
LU-C	0.819	0.722	0.694	1											
IB-C	0.653	0.667	0.645	0.626	1										
IB-N	0.646	0.644	0.607	0.634	0.744	1									
IB-S	0.654	0.646	0.631	0.634	0.835	0.807	1								
UK-C	0.707	0.716	0.646	0.695	0.693	0.717	0.709	1							
FR-C	0.720	0.649	0.699	0.786	0.663	0.666	0.678	0.676	1						
FR-N	0.676	0.678	0.626	0.652	0.730	0.812	0.768	0.749	0.677	1					
FR-S	0.688	0.685	0.662	0.670	0.811	0.754	0.783	0.717	0.756	0.735	1				
CH-C	0.701	0.631	0.856	0.669	0.622	0.569	0.600	0.590	0.701	0.590	0.655	1			
AT-C	0.651	0.615	0.848	0.602	0.604	0.545	0.561	0.571	0.634	0.570	0.625	0.851	1		
CZ-C	0.786	0.743	0.765	0.665	0.622	0.573	0.579	0.639	0.609	0.615	0.617	0.666	0.694	1	
PL-C	0.714	0.710	0.720	0.622	0.636	0.558	0.584	0.643	0.603	0.595	0.633	0.640	0.668	0.782	1
DK-C	0.738	0.810	0.670	0.698	0.702	0.696	0.695	0.750	0.677	0.717	0.727	0.616	0.594	0.667	0.674
SK-C	0.763	0.803	0.693	0.695	0.680	0.637	0.646	0.715	0.652	0.683	0.713	0.638	0.620	0.740	0.746
IT-C	0.729	0.733	0.744	0.680	0.768	0.688	0.730	0.711	0.696	0.700	0.798	0.718	0.699	0.700	0.729
IT-N	0.729	0.729	0.778	0.686	0.721	0.661	0.688	0.680	0.709	0.669	0.764	0.754	0.759	0.709	0.735
IT-S	0.683	0.693	0.682	0.622	0.714	0.620	0.670	0.653	0.636	0.649	0.730	0.650	0.649	0.681	0.723
ET-C	0.719	0.727	0.729	0.646	0.652	0.579	0.611	0.667	0.633	0.616	0.686	0.662	0.695	0.741	0.839
ET-N	0.703	0.739	0.650	0.626	0.626	0.568	0.577	0.666	0.603	0.606	0.677	0.592	0.601	0.689	0.722
ET-S	0.629	0.656	0.620	0.544	0.611	0.496	0.530	0.578	0.550	0.539	0.642	0.581	0.585	0.638	0.703

continued

	DK-C	SK-C	IT-C	IT-N	IT-S	ET-C	ET-N	ET-S
DK-C	1							
SK-C	0.786	1						
IT-C	0.750	0.755	1					
IT-N	0.722	0.752	0.841	1				
IT-S	0.711	0.728	0.836	0.771	1			
ET-C	0.710	0.773	0.776	0.800	0.766	1		
ET-N	0.739	0.807	0.717	0.720	0.703	0.741	1	
ET-S	0.667	0.716	0.742	0.705	0.771	0.751	0.690	1

Table 24: Correlation matrix for modeled solar and wind sites - daytime

		Wind														
		DE-C	DE-N	DE-S	LU-C	IB-C	IB-N	IB-S	UK	FR-C	FR-N	FR-S	CH-C	AT-C	CZ-C	PL-C
Solar	DE-C	**-0.228**	-0.175	-0.104	-0.262	-0.087	-0.045	-0.140	-0.230	-0.239	-0.064	-0.231	-0.211	-0.132	-0.198	-0.141
	DE-N	-0.205	**-0.175**	-0.205	-0.189	-0.042	-0.073	-0.192	-0.249	-0.152	-0.109	-0.200	-0.145	-0.185	-0.106	-0.186
	DE-S	-0.146	-0.223	**-0.104**	-0.149	-0.047	-0.100	-0.190	-0.166	-0.176	-0.203	-0.226	-0.230	-0.181	-0.140	-0.104
	LU-C	-0.247	-0.264	-0.170	**-0.262**	-0.061	-0.058	-0.215	-0.205	-0.252	-0.148	-0.270	-0.235	-0.167	-0.126	-0.128
	IB-C	0.003	-0.014	-0.034	-0.018	**-0.087**	-0.118	-0.137	-0.157	-0.045	-0.047	-0.112	-0.088	-0.035	0.042	-0.086
	IB-N	-0.043	-0.054	-0.035	-0.078	-0.076	**-0.045**	-0.200	-0.176	-0.108	-0.055	-0.163	-0.136	-0.030	0.013	-0.090
	IB-S	0.018	-0.020	-0.030	-0.007	-0.050	-0.057	**-0.140**	-0.158	-0.044	-0.039	-0.096	-0.114	-0.040	0.045	-0.093
	UK-C	-0.098	-0.087	-0.099	-0.171	-0.021	-0.053	-0.187	**-0.230**	-0.152	-0.085	-0.195	-0.166	-0.093	-0.008	-0.137
	FR-C	-0.141	-0.188	-0.103	-0.189	-0.106	-0.106	-0.206	-0.176	**-0.239**	-0.165	-0.298	-0.248	-0.081	-0.063	-0.071
	FR-N	-0.077	-0.080	-0.065	-0.111	-0.022	-0.039	-0.170	-0.202	-0.096	**-0.064**	-0.146	-0.124	-0.084	-0.002	-0.099
	FR-S	-0.040	-0.041	-0.045	-0.080	-0.156	-0.107	-0.192	-0.164	-0.147	-0.142	**-0.231**	-0.221	0.002	0.026	-0.076
	CH-C	-0.133	-0.213	-0.087	-0.158	-0.074	-0.120	-0.169	-0.153	-0.189	-0.204	-0.240	**-0.211**	-0.111	-0.100	-0.077
	AT-C	-0.118	-0.172	-0.076	-0.128	-0.086	-0.114	-0.185	-0.141	-0.159	-0.220	-0.216	-0.220	**-0.132**	-0.109	-0.069
	CZ-C	-0.184	-0.233	-0.171	-0.159	-0.052	-0.086	-0.195	-0.196	-0.154	-0.169	-0.191	-0.181	-0.286	**-0.198**	-0.159
	PL-C	-0.124	-0.175	-0.117	-0.121	-0.053	-0.105	-0.182	-0.195	-0.133	-0.172	-0.190	-0.167	-0.239	-0.156	**-0.141**
	DK-C	-0.125	-0.105	-0.138	-0.169	-0.040	-0.063	-0.205	-0.291	-0.146	-0.083	-0.203	-0.161	-0.087	-0.021	-0.149
	SK-C	-0.146	-0.159	-0.169	-0.155	-0.047	-0.086	-0.198	-0.254	-0.139	-0.105	-0.201	-0.157	-0.167	-0.087	-0.200
	IT-C	-0.048	-0.085	-0.056	-0.091	-0.108	-0.141	-0.184	-0.167	-0.141	-0.145	-0.232	-0.171	-0.057	-0.015	-0.116
	IT-N	-0.102	-0.133	-0.080	-0.146	-0.134	-0.139	-0.219	-0.189	-0.176	-0.173	-0.248	-0.219	-0.104	-0.069	-0.104
	ET-C	-0.124	-0.161	-0.110	-0.130	-0.074	-0.106	-0.199	-0.182	-0.134	-0.167	-0.212	-0.195	-0.204	-0.121	-0.117
	ET-N	-0.134	-0.140	-0.157	-0.150	-0.086	-0.119	-0.188	-0.257	-0.146	-0.107	-0.206	-0.169	-0.138	-0.075	-0.218
	ET-S	-0.043	-0.075	-0.044	-0.099	-0.107	-0.128	-0.172	-0.175	-0.107	-0.124	-0.190	-0.122	-0.058	-0.022	-0.079

continued

		Wind						
		DK-C	SK-C	IT-C	IT-N	ET-C	ET-N	ET-S
Solar	DE-C	-0.232	-0.301	-0.086	-0.269	-0.147	-0.161	-0.070
	DE-N	-0.201	-0.271	0.025	-0.118	-0.082	-0.136	-0.100
	DE-S	-0.111	-0.212	-0.051	-0.204	-0.127	-0.141	-0.059
	LU-C	-0.164	-0.230	0.030	-0.123	-0.108	-0.115	-0.088
	IB-C	-0.079	-0.251	0.026	-0.050	0.017	-0.085	-0.081
	IB-N	-0.073	-0.238	0.069	-0.047	-0.007	-0.102	-0.055
	IB-S	-0.066	-0.230	0.043	-0.033	0.002	-0.098	-0.068
	UK-C	-0.153	-0.234	0.065	-0.089	-0.032	-0.112	-0.087
	FR-C	-0.128	-0.217	0.010	-0.151	-0.060	-0.113	-0.090
	FR-N	-0.105	-0.249	0.076	-0.049	-0.019	-0.097	-0.084
	FR-S	-0.082	-0.263	0.026	-0.131	0.013	-0.080	-0.082
	CH-C	-0.104	-0.201	-0.088	-0.211	-0.090	-0.120	-0.062
	AT-C	-0.093	-0.187	-0.087	-0.233	-0.088	-0.121	-0.059
	CZ-C	-0.151	-0.238	-0.004	-0.164	-0.160	-0.149	-0.060
	PL-C	-0.139	-0.260	-0.032	-0.176	-0.189	-0.168	-0.074
	DK-C	**-0.232**	-0.299	0.047	-0.093	-0.035	-0.134	-0.114
	SK-C	-0.202	**-0.301**	0.010	-0.133	-0.086	-0.163	-0.122
	IT-C	-0.099	-0.262	**-0.086**	-0.237	-0.042	-0.128	-0.095
	IT-N	-0.112	-0.260	-0.147	**-0.269**	-0.091	-0.129	-0.080
	ET-C	-0.127	-0.262	-0.024	-0.214	**-0.147**	-0.178	-0.069
	ET-N	-0.217	-0.313	-0.011	-0.153	-0.088	**-0.161**	-0.170
	ET-S	-0.095	-0.243	-0.055	-0.160	-0.057	-0.252	**-0.070**

ABOUT EWI

EWI is a so called An-Institute annexed to the University of Cologne. The character of such an institute is determined by a complete freedom of research and teaching and it is solely bound to scientific principles. The EWI is supported by the University of Cologne as well as by a benefactors society whose members are of more than forty organizations, federations and companies. The EWI receives financial means and material support on the part of various sides, among others from the German Federal State North Rhine-Westphalia, from the University of Cologne as well as – with less than half of the budget – from the energy companies E.ON and RWE. These funds are granted to the institute EWI for the period from 2009 to 2013 without any further stipulations. Additional funds are generated through research projects and expert reports. The support by E.ON, RWE and the state of North Rhine-Westphalia, which for a start has been fixed for the period of five years, amounts to twelve Million Euros and was arranged on 11th September, 2008 in a framework agreement with the University of Cologne and the benefactors society. In this agreement, the secured independence and the scientific autonomy of the institute plays a crucial part. The agreement guarantees the primacy of the public authorities and in particular of the scientists active at the EWI, regarding the disposition of funds. This special promotion serves the purpose of increasing scientific quality as well as enhancing internationalization of the institute. The funding by the state of North Rhine-Westphalia, E.ON and RWE is being conducted in an entirely transparent manner.