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Optimization of power plant investments under uncertain renewable energy deployment paths - A multistage stochastic programming approach

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Abstract

Electricity generation from renewable energy sources (RES-E) is supposed to increase significantly within the coming decades. However, uncertainty about the progress of necessary infrastructure investments, public acceptance and cost developments of renewable energies renders the achievement of political plans uncertain. Implementation risks of renewable energy targets are challenging for investment planning, because different RES-E shares fundamentally change the optimal mix of dispatchable power plants. Specifically, uncertain future RES-E deployment paths induce uncertainty about the steepness of the residual load duration curve and the hourly residual load structure. In this paper, we show how uncertain future RES-E penetrations impact the electricity system and try to quantify effects for the Central European power market. We use a multi-stage stochastic investment and dispatch model to analyze effects on investment choices, electricity generation and system costs. Our main findings include that the uncertain achievement of RES-E targets significantly effects optimal investment decisions. First, a higher share of technologies with a medium capital/operating cost ratio is cost-efficient. Second, the value of storage units in systems with high RES-E penetrations might decrease. Third, in the case of the Central European power market, costs induced by the implementation risk of renewable energies seem to be rather small compared to total system costs.

Keywords: Multi-Stage Stochastic Programming, Renewable Energy, Power Plant Optimization

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1. Introduction

In order to reduce CO_2 emissions and the dependency from imported fuels, many countries established ambitious targets to increase electricity generation from renewable energy sources (RES-E). European Member States agreed to increase the European RES-E share from 15.6% in 2007 to 34% in 2020. Although long-term targets (after 2020) have not been defined on a European level, individual Member States, such as Germany, target to increase their RES-E shares continously up to 80% in 2050.

However, the implementation of political plans can be uncertain even if reliable targets exist, for four principal reasons. First, many RES-E technologies are relatively new technologies implying that technological and cost developments are uncertain and/or that limited experiences exist for construction and maintenance. Second, favorable RES-E sites are often located far from demand centers and therefore the electricity network has to be adapted. Third, local opposition may hinder the construction of new sites or transmission lines due to visual or environmental concerns. Fourth, when RES-E is supported by a price-based promotion system, such as by a feed-in-tariff system, resulting RES-E quantities are inherently uncertain.

Uncertainty about the achievement of RES-E targets is challenging for investment planning, because different RES-E shares fundamentally change the optimal mix of dispatchable power plants. Specifically, uncertain future RES-E deployment paths induce uncertainty about the steepness of the residual load duration curve and the structure of the hourly residual load. Thus, the optimal mix of (dispatchable) peak-, mid- and baseload plants is uncertain. In addition, it is uncertain how flexible the power plant fleet should optimally be and how valuable storage units are for the system. Consequently, the optimal investment planning for power plants with long construction, amortization and lifetimes is difficult.

In this paper, we show in a first part how uncertain future RES-E penetrations impact the electricity system and in a second part try to quantify this impact from a social wefare perspective for the electricity systems of Germany and its neighboring countries. For the second part, we assume that a continuous increase of the RES-E share until 2050 is a reliable target which is however submitted to risks about the progress of necessary infrastructure investments, public acceptance and cost developments of RES-E. We use a multi-stage stochastic investment and dispatch model to quantify effects on investment choices, electricity generation and system costs.

Our main findings include that the uncertain achievement of RES-E targets significantly effects optimal investment decisions. First, a higher share of technologies with a medium capital/operating cost ratio is cost-efficient. Second, the value of storage units in systems with high RES-E penetrations might decrease.

Third, in the case of the Central European power market, costs induced by the implementation risk of renewable energies seem to be rather small compared to total system costs.

The remainder of the article is structured as follows: The next section provides an overview of related literature and the contribution of the current work. Section 3 describes the modeling approach and gives an overview of assumed input parameters. In Section 4 we discuss theoretically the impact of uncertain future RES-E penetrations and highlight the most important effects in an illustrative modeling example. In Section 5 we quantify the impact of uncertain RES-E target achievement for the electricity systems of Germany and its neighboring countries. In Section 6 we draw conclusions and provide an outlook for further research.

2. Related literature and contributions of the current work

The analysis of uncertainties with help of stochastic optimization models can be traced back to the 1950´s (Dantzig (1955)). Applications to electricity investment planning models often focus on the effects of demand, fuel or CO_2 emission prices. In recent years also the influence of intermittent renewable infeed on investment decisions for conventional power plants has been analyzed with stochastic optimization models.

The influence of demand uncertainty on investment decisions has been first shown in the 1980´s for example by Murphy et al. (1982) and Mondiano (1987). Gardner (1996) and Gardner and Rogers (1999) analyze the effect of demand uncertainty in dynamic contexts, using multistage optimization models.[1] Gardner (1996) shows that the value of technologies with short lead times, short lifetimes and/or a low capital/operating cost ratio increases in an uncertain environment. Gardner and Rogers (1999) analyze in more detail the effect of short lead times when dealing with demand uncertainty.

Uncertainty about fuel costs have been adressed e.g. by Hobbs and Maheshwari (1990), showing that expected costs of neglecting uncertainty of fuel prices in investment planning is lower than those of disregarding demand uncertainties. Reinelt and Keith (2007) use a stochastic dynamic model to analyze generation technology choices and optimal timing in investment when future CO_2 and natural gas prices are uncertain. Roques et al. (2006) evaluate investment decisions into nuclear and CCGT plants under uncertainty about natural gas, CO_2 emission and electricity prices by applying a multi-stage stochastic programm. Effects of uncertain future CO_2 regulations are also adressed by Patino-Echeverri et al. (2009) who apply a stochastic dynamic model and analyze the effect of uncertainty on investment strategies, social costs and CO_2 emissions.

[1] For different applications, dynamic stochastic electricity optimization models have been developed before, e.g. by Manne and Richels (1978).

Short-term uncertainties about the infeed of intermittent renewables have been analyzed in stochastic investment and dispatch models e.g. by Swider and Weber (2006) and Sun et al. (2008). Swider and Weber (2006) use a stochastic model to estimate the integration costs of wind´s intermittency and show that larger investments into thermal capacities are required when short-term stochastics of wind infeed are taken into account. This result is confirmed by Sun et al. (2008) who find that neglecting short-term uncertainties about wind infeed leads to an undervaluation of the operational flexibility and results in insufficient investments of thermal power plants.

In contrast to the analysis of short-term uncertain renewable infeed, we analyze the influence of long-term uncertain renewable penetrations induced by uncertainty about the achievement of political RES-E targets. To our knowlegde, the impact of long-term uncertain residual load developments on the power system has not been analyzed so far. Other long-term uncertainties, e.g. about demand, fuel or CO_2 emission price developments, either primarily correspond to uncertainty about how much capacity should be optimally constructed (demand) or induce uncertainty about the optimal technology mix (fuel and CO_2 emission prices). In the context of uncertain future RES-E penetrations both, the optimal amount of dispatchable generation capacities and the optimal technology mix is uncertain, because the level and the slope of the future residual load duration curve as well as the volatility of the hourly residual load curve are unknown.

3. Model description and assumptions

In this section we describe the stochastic optimization model (3.1) and present the major assumptions underlying the scenario analysis (3.2).

3.1. Model description

We use a linear multistage stochastic investment and dispatch model for electricity markets. The model covers thermal and nuclear plants as well as storage units. In each model period, different nodes account for different possible realizations of the residual load. In the following, we present the basic model equations and describe how uncertainty is captured in the model. Used abbreviations for model sets, parameters and variables are shown in Table 1.[2]

[2] The table only shows sets, parameters and variables used in the equations listed within this chapter. In addition, the model comprises e.g. additional variables necessary for ramping or storage equations such as the hourly storage level in a storage unit.

Table 1: Model abbreviations including sets, parameters and variables

Abbreviation	Dimension	Description
Model sets		
d		Day
h		Hour
n		Node
n1	alias of n	Node (direct ancestor of n)
n2	alias of n	Node (direct or indirect ancestor of n)
r		Region
r1	alias of r	Neighboring region of r
res		RES-E technology
s	Subset of t	Storage technology
t		Technology
y	Subset of n	Node (associated with a certain model year)
Model parameters		
ad	MW	Exogenous capacity commissions
annuity	€$_{2010}$/MW	Technology specific investment costs (annuity)
attc	€$_{2010}$/MWh$_{th}$	Attrition costs for ramp-up operation
co	€$_{2010}$/t CO_2	CO_2 emissions prices
cres	MW	RES-E capacities
dsc	%	Discount factor
f	€$_{2010}$/MWh$_{th}$	Fuel prices
fomc	€$_{2010}$/MW	Fixed operation and maintenance costs
heatpr	€$_{2010}$/MWh$_{th}$	Heating price for end consumers
heatratio	MWh$_{th}$/MWh$_{el}$	Ratio for heat extraction
p	%	Occurence probability of node
β	%	Minimum generation level of power plants
η	%	Net efficiency
$\eta_{partload}$	%	Net efficiency in partload operation
ρ	MW	Residual demand
θ	MW	Peak demand
τ	%	Capacity factor
γ	%	Capacity factor (RES-E plants)
ω	t CO_2 /MWh$_{th}$	CO_2 emissions per fuel consumption
Model variables		
C	MW	Installed capacity (net)
CADD	MW	Capacity commissions (net)
CRTO	MW	Capacity which is ready to operate (net)
CSUB	MW	Capacity decommissions (net)
CUP	MW	Ramped-up capacity (net)
G	MW	Electricity generation (net)
NI	MW	Net imports
S	MW	Consumption in storage operation
Z	€$_{2010}$	Total system costs (objective value)

The objective of the model is to minimize total discounted system costs (equation 1) while satisfying (residual) demand (eq. 2) and ensuring that peak demand can be met by securely available capacities in each node (eq. 3). Equation 4 determines the capacity in each node which depends on investment decisions made in previous periods and thus under uncertainty about the level and the structure of the residual load.

$$
\begin{aligned}
min\ Z = \sum_n \Bigg[p(n) \cdot dsc(y) \cdot \sum_{t,r} \Bigg[\Bigg[\sum_{n1} annuity(t) \cdot CADD(t,n1,r) \Bigg] + C(t,n,r) \cdot fomc(t) \\
+ \Bigg[\sum_{d,h} G(d,h,n,t,r) \Bigg] \cdot \Bigg[\frac{f(y,t) + co(y) \cdot \omega(t)}{\eta(t)} \Bigg] \\
+ \Bigg[\sum_{d,h} CUP(d,h,n,t,r) \Bigg] \cdot \Bigg[\frac{f(y,t) + co(y) \cdot \omega(t)}{\eta(t)} + attc(t) \Bigg] \\
+ \Bigg[\sum_{d,h} (CRTO(d,h,n,t,r) - G(d,h,n,t,r)) \Bigg] \cdot \Bigg[\frac{f(y,t) + co(y) \cdot \omega(t)}{\eta_{partload}(t)} - \frac{f(y,t) + co(y) \cdot \omega(t)}{\eta(t)} \Bigg] \cdot \frac{\beta}{1-\beta} \\
- \sum_{d,h} heatpr(y) \cdot heatratio(t) \cdot G(d,h,n,t,r) \Bigg] \Bigg]
\end{aligned} \tag{1}
$$

s.t.

$$
\sum_t G(d,h,n,t,r) + \sum_{r1} NI(d,h,n,r,r1) - \sum_s S(d,h,n,s,r) = \rho(d,h,n,r) \tag{2}
$$

$$
\tau \cdot C(t,n,r) + \gamma \cdot cres(res,n,r) \geq \theta(n,r) \tag{3}
$$

$$
C(t,n) = \sum_{n2} \Bigg[C(t,n2) + CADD(t,n2) \Bigg] + ad(t,y) - CSUB(t,n) - \sum_{n1} \Bigg[CADD(t,n1) + ad(t,n1) \Bigg] \tag{4}
$$

Total system costs comprise fix costs (investment and fixed operation and maintenance costs), variable production costs including fuel and CO_2 costs, ramp-up costs and costs arising due to efficiency losses in part-load operation. We simulate ramp-up costs in this linear approach by referring to power plant vintage classes and setting a minimal load restriction and additional costs for ramping-up (attrition (*attc*) and extra fuel costs). In part-load operation fuel costs of power plants are higher due to lower efficiency values, which is taken into account by a linear approximation. A heat remuneration for electricity generation in co-generation mode is subtracted from total system costs. The heat remuneration corresponds to the assumed gas price (divided by the conversion efficiency of the assumed reference heat boiler) which roughly represents the opportunity costs for households and industries. Heat generation in co-generation plants is restricted by a maximum heat potential per country and the inflexibility of electricity generation in co-generation mode is represented by longer ramping times. All cost parameters are taken into account with the occurrence probability $p(n)$ of the node n in which the costs arise.

The hourly residual demand per country and node, inflows to storage units and electricity exports have to be met by generation from thermal, nuclear and storage plants and/or by electricity imports (eq.2). The dispatch within each node is calculated for four typical days, representing a weekday and a weekend-day in autumn/winter respectively spring/summer. Note that the model includes only long-term uncertainties about the deployment of RES-E capacities and no short-term uncertainty about the hourly infeed of renewables. The dispatch of generation and demand is realized under perfect foresight.

Peak demand (augmented by a security margin) per country and node has to be ensured by installed capacities which are securely available at times of peak demand (eq.3).[3] Thermal, nuclear and storage capacities are accounted with a factor incorporating possible outages (planned or not planned; in the range of 85-90 percent). Fluctuating RES-E contribute with a relatively low capacity credit (5% for wind, 0% for photovoltaics).

Equation 4 determines the capacity in node n depending on the installed capacity and the investment decisions made in its ancestor node n2. In addition, the installed capacity in node n is augmented by exogenous capacity commissions (representing thermal, nuclear and storage power plants which today are already under construction or in an advanced planning process) and reduced by capacity decommissions, before or at the end of the technical lifetime of plant t. Thus, the model takes into account that power plant investments have long planning, construction, amortization and lifetimes. The effect of long planning and construction times is captured by the fact that investment decisions have to be made one period before their commissioning and thus under uncertainty about the state of the world at commissioning time. The effect of long amortization and lifetimes in uncertain environments is captured by the fact that when an investment decision for a power plant is made, states of the world until the end of its lifetime are uncertain.

Apart from the basic equations, the model incorporates all common elements of linear dispatch models such as storage equations, ramping and minimum load restrictions, net transfer possibilities and the possibility of RES-E curtailment.

3.2. Assumptions

In the following we present the major assumptions underlying the scenario analysis. For the illustrative example (Section 4), cost assumptions for the year 2020 are used. For the analysis of RES-E implementation risks on the electricity systems of Germany and its neighboring countries (Section 5), we model Germany,

[3] The peak demand corresponds to the highest demand before subtraction of fluctuating RES-E in-feed.

Benelux (covering Belgium, the Netherlands and Luxembourg), Denmark, Czech Republic and Poland (”CZ + PL”), Switzerland and Austria (”CH + AT”) and France.

3.2.1. Electricity demand and potential heat generation in combined-heat-and-power (CHP) plants

Electricity demand is primarily driven by economic and population growth. Furthermore, improvements in energy efficiency and the emergence of new technologies (such as electric cars) impact the development of the electricity consumption. Based on these considerations, we assume that electricity demand will increase until 2030 and stagnate afterwards. In addition to electricity demand values, Table 2 reports values for heat demand, based on figures for electricity production in co-generation reported in Eurelectric (2008). In order to reduce computational time, the option to generate electricity in combined-heat-and-power (CHP) plants is restricted to countries in which CHP based electricity generation makes up a major part of todays electrictiy generation.

Table 2: Net electricity demand in TWh_{el} and (potential heat generation in CHP Plants in TWh_{th})

	2020		2030		2040		2050	
Benelux	226.2	(128)	241.7	(128)	241.7	(128)	241.7	(128)
CH + AT	140	(-)	149.5	(-)	149.5	(-)	149.5	(-)
CZ + PL	233.9	(146)	260.4	(146)	260.4	(146)	260.4	(146)
Denmark	43.1	(54)	46	(54)	46	(54)	46	(54)
Germany	611	(191)	628	(191)	628	(191)	628	(191)
France	523.6	(-)	558.3	(-)	558.3	(-)	558.3	(-)

3.2.2. Power plants

Table 3 depicts assumed investment costs for thermal, nuclear and storage technologies. In addition to the listed technologies, the model comprises several technology classes to account for existing power plants. Investments into nuclear, hard coal, lignite, open-cycle-gas-turbines (OCGT), combined-cycle-gas-turbines (CCGT) and compressed-air-storages (CAES) are possible. Investments into nuclear plants are restricted to countries which already have existing nuclear power plants and which did not agree on a political phase-out of nuclear power. In addition, before 2025 only nuclear plants already under construction today can be built due to long planning and construction times. For hard coal and lignite, state-of-the-art and innovative power plants are considered in the model. Innovative hard coal plants are equipped with improved materials and process techniques and thus able to run at 700 degrees celsius and higher pressures (350 bars) than existing plants. The efficiency is assumed to increase by about 4 percentage points to 50% due to these improvements. Investment costs are above state-of-the-art technologies but are decreasing due to learning effects by around a third until 2050. ”Innovative” lignite technologies use a more efficient drying process than existing plants and can therefore increase their efficiency to 48%. Hard coal, lignite and CCGT plants can also be build as CHP technologies. The investment costs of CHP plants include additional costs for the grid and the extraction of heat. Due to the limited space potential, pump storage and hydro storage plants are not an investment option.

Table 3: Investment costs of conventional and storage technologies in €$_{2010}$/kW

Technologies	2020	2030	2040	2050
Nuclear	3,157	3,157	3,157	3,157
Hard Coal	1,500	1,500	1,500	1,500
Hard Coal - innovative	2,250	1,875	1,750	1,650
Hard Coal - innovative CHP	2,650	2,275	2,150	2,050
Lignite - innovative	1,950	1,950	1,950	1,950
Lignite - innovative CHP	2,350	2,350	2,350	2,350
OCGT	400	400	400	400
CCGT	800	800	800	800
CCGT-CHP	1,100	1,100	1,100	1,100
Pump storage	-	-	-	-
Hydro storage	-	-	-	-
CAES	850	850	850	850

Table 4 shows the efficiency grades (at optimal operation and when operating at minimum load level), technical availability, operational and maintenance costs and the technical lifetime for conventional plants. Depicted efficiency grades correspond to those of newly constructed plants. CHP plants have lower electrical but higher total efficiency grades than plants without co-generation option. For CHP plants, operational and maintenance costs also include the costs for the heat extraction system. The availability factor reported in Table 4 represents the average value of the four seasonal availability factors in the model and accounts for planned and unplanned shut-downs of the plants, e.g. because of revisions. In addition, the availability factor determines the contribution of thermal, nuclear and storage plants to the securely available capacity at times of peak demand. For exogenously treated renewable plants we assume a contribution to securely available capacity of 5% for wind and 0% for solar plants. Biomass and geothermal capacities are dispatchable plants and accounted with a capacity credit of 80%.

Assumed CO_2 factors (in t CO_2 /MWh_{th}) are 0.406 for lignite fired plants, 0.335 for hard coal fired plants and 0.201 for gas fired plants.

Table 4: Economic-technical parameters for conventional and storage technologies

Technology	$\eta(\eta_{load})$ [%]	η_{min} [%]	availability [%]	FOM-costs [€$_{2010}/kW$]	Lifetime [a]
Nuclear	33.0	28.0	84.5	96.6	50
Hard Coal	46.0	41.0	83.75	36.1	40
Hard Coal - innovative	50.0	45.0	83.75	36.1	40
Hard Coal - innovative CHP	22.5	17.5	83.75	55.1	40
Lignite - innovative	46.5	41.5	86.25	43.1	40
OCGT	40.0	20.0	84.5	17	20
CCGT	60.0	50.0	84.5	28.2	30
CCGT-CHP	36.0	26.0	84.5	40	30
Pump storage	87.0 (83.0)	87.0	95.25	11.5	100
Hydro storage	87.0	87.0	90.75	11.5	100
CAES	86.0 (81.0)	86.0	95.25	9.2	30

We assume that yearly lignite assumption is restricted to 350 TWh$_{th}$ in Germany and to 249 TWh$_{th}$ in the region Czech Republic and Poland. In the other model regions, lignite is not a generation option because the low calorific value and high moisture content of lignite leads to prohibitively high transportation costs of lignite.

3.2.3. Fuel and CO_2 emission prices

Table 5 lists the assumed development of fuel prices (including transportation costs to the power plants) together with historical prices. After the high price year 2008, fuel prices have come down rapidely and started to rebound afterwards. Assumptions concerning the fuel price development are mainly based on EWI/energynautic (2011). Regarding CO_2 prices, we assume that more restrictive quotas will lead to increasing prices while an increasing RES-E share attenuates this effect. Overall, we assume that the CO_2 price increases up to 45 €$_{2010}$/t CO_2 in 2050.

Table 5: Fuel costs in €$_{2010}$/MWh$_{th}$ and CO_2 emission costs in €$_{2010}$/t CO_2

	2008	2020	2030	2040	2050
Oil	44.6	99.0	110.0	114.0	116.0
Coal	17.28	13.4	13.8	14.3	14.7
Natural Gas	25.2	28.1	30.1	32.1	34.1
Lignite	1.4	1.4	1.4	1.4	1.4
Uranium	3.6	3.3	3.3	3.3	3.3
CO_2	22	25	35	40	45

3.2.4. Net transfer capacities

Table 6 depicts assumed net tranfer capacities (NTC), restricting im- and exports between model regions. Assumptions are based on ENTSO-E (2010). For model regions representing several countries, such as

Benelux, the NTC-values of the represented countries have been summed up.

Table 6: Net transfer capacities [MW]

	DE	FR	Benelux	CH+AT	CZ+PL	DK
DE	-	3050	4830	3100	1600	1500
FR	2600	-	2900	3000	-	-
Benelux	3980	1300	-	-	-	-
CH+AT	4800	1100	-	-	600	-
CZ+PL	3200	-	-	800	-	-
DK	2050	-	-	-	-	-

4. Theoretical discussion of effects and illustrative example

In this section we discuss the influence of RES-E infeed on the optimal electricity capacity mix, the effects of uncertainty about future RES-E penetrations and means to measure these effects (Section 4.1). In addition, we highlight the impact of uncertain future RES-E deployment paths in an illustrative modeling example (Section 4.2).

4.1. Theoretical discussion of results

Uncertainty about future RES-E penetrations leads to uncertainty about the residual demand, which has to be met by thermal and nuclear plants or by storage units. Figure 1 illustrates the influence of RES-E infeed on the optimal mix of dispatchable power plants. The upper graph depicts an hourly load curve without and after substraction of RES-E infeed. The middle graph shows the corresponding (residual) load duration curves and the lower graph depicts the optimal mix of peak-, mid- and baseload plants depending on their yearly utilization times.[4]

[4] An electricity load duration curve ranks load levels in a descending order of magnitude. The integral under the load duration curve shows, how much electricity is demanded for how many hours per year. For the fraction of demand, which is needed in nearly all hours of the year, plants with high fix and low variable costs (baseload plants) are cost-efficient while demand peaks are cost-efficiently met by peakload plants, characterized by high variable but low fix costs (see e.g. Stoft (2002)).

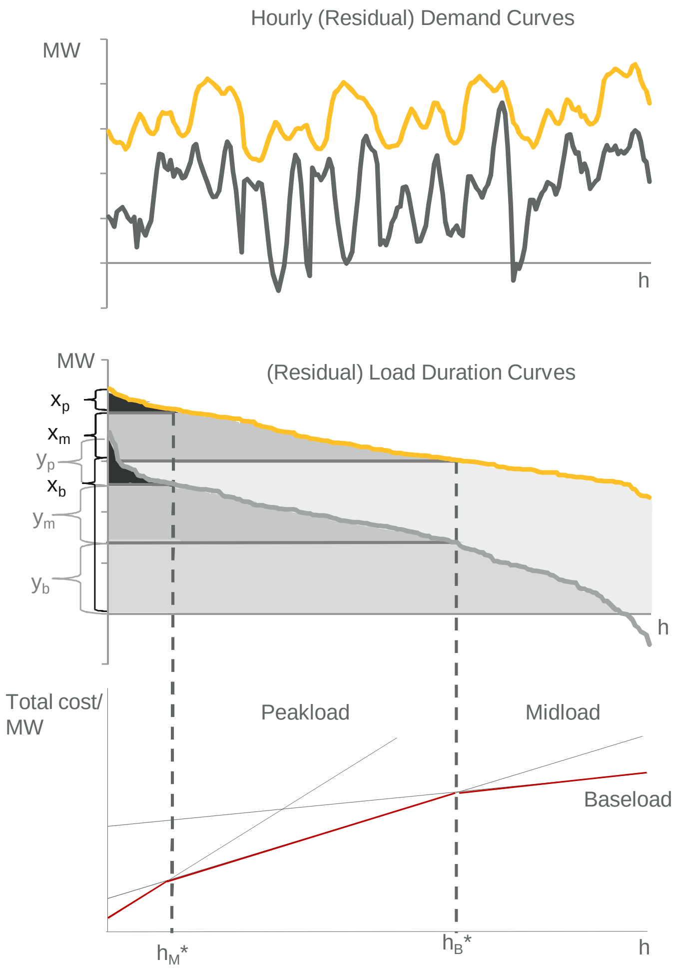

Figure 1: Effects of RES-E infeed on the optimal capacity mix

With high infeed from renewables, the residual load duration curve becomes steeper. In many hours, a large part of the (residual) demand is met by renewables with negligible variable generation costs. Thus, the (residual) demand fraction which is constantly high in almost all hours of the year shrinks. Consequently, the optimal capacity mix comprises less baseload plants which need high utilization times in order to be cost-efficient ($y_b < x_b$). In addition, these baseload plants achieve lower utilization times than without RES-E infeed, due to a steeper residual load curve in the area of higher utilization times than h_B^*. On the other hand, fluctuating RES-E such as wind and solar plants are not necessarily available at times of high demand. Thus, high electricity demands still need to be met by dispatchable power plants and the optimal capacity mix comprises a larger amount of peak- and midload capacities ($y_p > x_p$ and $y_m > x_m$) when RES-E shares are high (see also Lamont (2008) and DeJonghe et al. (2011)).[5] This effect is further increased considering security of supply requirements (not depicted in Figure 1). Due to low capacity credits of fluctuating RES-E, a large share of dispatchable generation capacities are also needed in electricity systems with high RES-E penetrations, in order to ensure that peak demand can be met with securely available capacities (see e.g. Dena (2008) and Weigt (2009)).

In addition, the volatility of the hourly residual load curve increases with a higher RES-E share (upper graph). Consequently, with an increasing RES-E share, the economic value of power plants with short ramping times increases. Plants with a high capital/operating cost ratio are also those plants characterized by long ramping times while plants with a low capital/operating cost ratio, such as open cycle gas turbines, can be ramped up and down within short time frames. Consequently, the effect of an increasing (decreasing) economic value of peakload (baseload) plants due to the steeper residual load curve, is increased by changing ramping requirements. Also storage units have a higher economic value if demand volatility increases (see e.g. Nagl et al. (2011)).

For these reasons, under uncertainty about future RES-E penetrations, it is uncertain whether the optimal electricity mix should comprise large shares of baseload or rather large shares of peakload plants and storage units. Means to measure the impact of this uncertainty on electricity system costs are the expected value of perfect information (EVPI) and the value of the stochastic solution (VSS). The EVPI determines the expected additional costs induced by uncertainty, if the uncertainty is taken into account by a stochastic optimization procedure. The VSS corresponds to the additional costs (compared to the stochastic solution) arising when investments are planned for the average realization of the random parameters (here: residual load curves), without taking into account uncertainty. Thereby the VSS measures, how much stochastic optimization can help to mitigate effects of uncertainty (Birge and Louveaux (1997)).

4.2. Illustrative example

In the following we present an illustrative modeling example in order to highlight effects of uncertain future RES-E deployment paths on optimal investment choices (4.2.1) and system costs (4.2.2). We consider one model region without existing power plant fleet and only two time periods. Furthermore, for reasons of simplicity we assume in this illustrative example that the contribution of RES-E to security of supply requirements is zero.

[5] One exception to this general impact of an increasing RES-E share on the slope of the residual load duration curve exists for small shares of renewables whose infeed matches well with demand - i.e. small shares of solar based generation in countries with demand peaks at noon, when solar radiation is also highest. In these cases, an increasing RES-E share (up to a certain level) can even flatten the residual load duration curve.

4.2.1. Effects of uncertainty on the optimal technology mix

In this illustrative example, investment decisions have to be made in period 0 under uncertainty about the RES-E penetration in period 1, when RES-E shares of 0% (S1), 25% (S2) and 50% (S3) can be realized with equal probability. Investments are possible into hard coal, CCGT and OCGT plants, representing a baseload, a midload and a peakload technology. In addition, investments into storage units can be made. Table 7 shows the investment decisions for each of the three branches given perfect information about their realizations and the stochastic solution given uncertainty about RES-E penetrations in period 1. In addition, utilization times are depicted.

Table 7: Investments [GW] and utilization times [h] with deterministic and stochastic planning

	S1 (0% RES-E)		S2 (25% RES-E)		S3 (50% RES-E)		stochastic			
	GW	h	GW	h	GW	h	GW	h		
Coal	83	6,969	61	6,869	41	6,660	50	7111 (S1);	6985 (S2);	5393 (S3)
CCGT	11	3,321	9	3,869	4	4,828	36	6455 (S1);	2792 (S2);	230 (S3)
OCGT	2	124	26	172	46	54	13	2248(S1);	0 (S2);	0 (S3)
Storage	8	1,191	7	1,377	15	1,188	5	1280 (S1);	647 (S2);	581 (S3)

It can clearly be seen, that the optimal deterministic power plant mixes vary significantly between the scenarios. In scenario S1, without RES-E infeed, the capacity mix is dominated by coal capacities while in scenario S3, with a 50% RES-E share, OCGT plants make up the largest share of capacities. Storage capacities are deployed to the largest extent in scenario S3, characterized by the most volatile residual load.[6] Taking into account these uncertainties by a stochastic optimization approach, resulting investments comprise more CCGT plants than in all deterministic scenarios. Investments into coal, OCGT and storage capacities are in contrast lower than on average within the deterministic scenarios.

CCGT plants are beneficial under uncertainty because - under the assumed fuel and CO_2 prices - they have a medium capital/operating cost ratio compared to coal and OCGT plants. Figure 2 depicts generation costs of coal, CCGT and OCGT plants (including annuitized capital costs and variable generation costs), depending on their utilization times. In the case of a high RES-E penetration, when CCGT plants have a low utilization and replace a part of the OCGT plants mainly built in order to ensure security of supply, additional generation costs of CCGT plants are relatively low compared to additional costs arising if coal plants would be mainly used for backup purposes. In the case of a low RES-E penetration, when CCGT plants have a high utilization and substitute a part of coal generation, additional generation costs of CCGT

[6] It might seem surprising that the optimal storage capacities in scenario S2 are lower than in S1 although the RES-E share is higher. The reason is that a large part of the RES-E infeed in S2 matches well with demand and even flattens demand peaks at noon time due to photovoltaic infeed. Although wind infeed does not match well with demand at all times, the infeed in scenario S2 does not lead to residual loads close to zero or even to negative residual loads such as in Scenario S3.

plants are relatively low compared to additional costs arising if a large part of demand would have to be provided by OCGT plants.

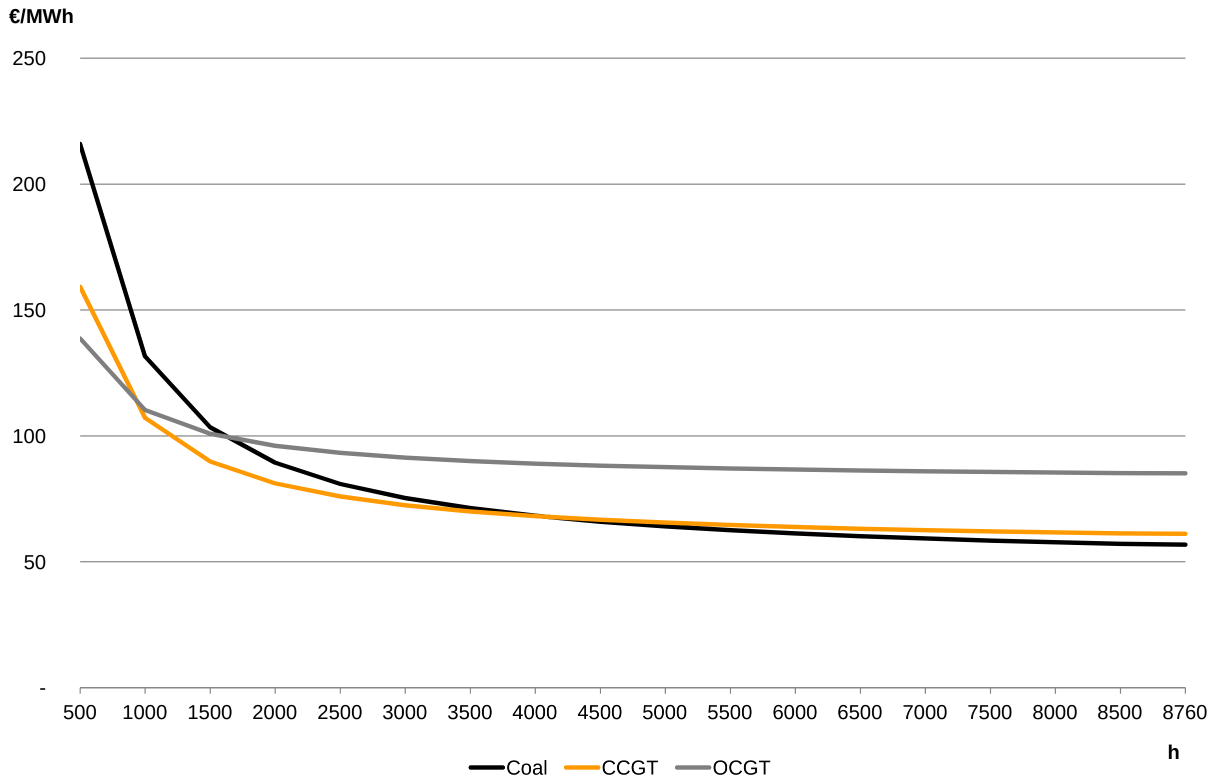

Figure 2: Generation costs of coal, CCGT and OCGT plants (depending on utilization times)

Reasons why storage units are deployed to a smaller extent under uncertainty are twofold. First, storage units are technologies which - similar to coal and OCGT plants - are primarily beneficial in some deterministic scenarios but have a low value if other scenarios are realized. Second, under stochastic planning, the high value storage units have in some scenarios under deterministic planning, nearly disappears. Due to a steep residual load duration curve and a high volatility of the hourly residual load in scenario S3, it is cost-efficient to install a larger share of CCGT and OCGT plants than in other scenarios. Thus, electricity prices are high during (residual) demand peaks, when plants with high variable generation costs are dispatched, and low during hours with a high RES-E infeed. This high volatility of electricity prices renders a significant number of storage units cost-efficient. Under stochastic planning, the optimal capacity mix comprises more coal and CCGT plants than in the deterministic S3 scenario and OCGT plants are not dispatched at all. Thus, under stochastic planning, the value for storage units is low within S3 because electricity prices have a lower volatility than under deterministic investment planning.[7] In addition it is important to note that the model incorporates the option of cost-efficient RES-E curtailment. Thus, a smaller amount of storage units installed under uncertainty does not necessarily increase the ramping requirements for thermal power plants. In this example, RES-E curtailment in scenario S3 in the stochastic solution is 4 TWh while a curtailment of 2 TWh is cost-efficient in the case of deterministic investment planning.

4.2.2. Effects of uncertainty on system costs

Table 8 depicts system costs (excluding costs for RES-E generation) arising in this illustrative scenario when the future is perfectly well known (deterministic planning), in the case of uncertainty under stochastic planning and in the case of uncertainty when the uncertainty is not taken into account within the investment planning process (average planning).

Table 8: System costs (exc. costs for RES-E generation) in Mio €, EVPI and VSS

	det planning	stoch planning	av planning
S1 (0% RES-E)	41,166	42,040	43,966
S2 (25% RES-E)	31,253	31,736	31,285
S3 (50% RES-E)	21,960	23,269	23,105
average costs	31,460	32,348	32,785
EVPI	889		
EVPI (% of det costs)	2.82%		
VSS	437		
VSS (% of det costs)	1.39%		

In all scenarios total system costs are higher under stochastic planning than under certainty (deterministic planning). In scenarios S1 and S2 a lower coal generation than under certainty leads to increasing variable generation costs. However, capital costs are lower, such that in sum total system costs increase by 1.5 - 2%. In scenario S3 total system costs under uncertainty are 6% higher than under certainty because lower variable costs do not outweigh additional capital costs. The EVPI, corresponding to the probability weighted additional costs arising in all scenarios under stochastic compared to deterministic planning, amounts to 889 Mio € respectively to 2.82%, expressed as percentage of average deterministic system costs.

The VSS, evaluating the benefit of solving the stochastic solution, is difficult to measure, because - due to different structures of the residual load curves and thus different ramping requirements - a planning for the average residual load curve does not guarantee that demand can be met in all scenarios. When we optimize

[7] In scenario S1 in contrast, stochastic planning leads to a high OCGT generation compared to the deterministic case. Electricity prices have a higher volatility than under deterministic planning and the 5 GW storage capacity, installed under uncertainty, consequently has its highest utilization time in S1.

capacities for the average residual load under the additional constraint that emand also needs to be met in all other possible scenarios, the VSS amounts to 437 Mio €, representing 1.39% of average deterministic system costs.[8] Expressed differently, approximately one third of all costs arising due to uncertainty about future RES-E penetrations can be avoided, by taking into account that the uncertainty exists.

5. Analysis of uncertain RES-E deployment paths in Germany and its neighboring countries

In the previous chapter we have shown, how uncertainty about future RES-E deployment paths changes optimal investment plans for thermal power plants and storage units and that this uncertainty induces additional costs. However, the remaining question is how significant these effects are in real-world electricity systems. In this context, it is important to exactly define the source of uncertainty which is analyzed and to determine possible bandwidth of realizations of the uncertain parameters according to this definition. Specifically, uncertain future RES-E deployment paths have two potential sources: Political uncertainty and uncertainty about the implementation of political plans. Political uncertainty arises when political targets are unclear or when it is uncertain, whether targets will be changed e.g. after governmental elections. The implementation of political plans can be uncertain even if reliable targets exist, for four principal reasons. First, many RES-E technologies are relatively new technologies implying that technological and cost developments are uncertain and/or that limited experiences exist for construction and maintenance. Second, favorable RES-E sites are often located far from demand centers and therefore the electricity network has to be adapted. Third, local opposition may hinder the construction of new sites or transmission lines due to visual or environmental concerns. Fourth, when RES-E is supported by a price-based promotion system, such as by a feed-in-tariffs system, resulting RES-E quantities are inherently uncertain.

In the following, we try to quantify effects of uncertainty about the implementation of reliable long-term political RES-E targets for Germany and its neighboring countries. We assume that a continuous increase of RES-E until 2050 is a politically agreed and reliable target for Germany and its neighboring countries.[9] Thus, we assume that the RES-E share increases within each model year and that only the magnitude of the increase is uncertain because the progress of necessary infrastructure investments, public acceptance, cost and technological developments of renewable energy technologies can´t be perfectly foreseen.

[8] In this auxiliary average residual load scenario, dispatch costs are only taken into account for the average residual load scenario. However, chosen capacities have to be sufficient in order to meet demand in all scenarios.

[9] It is important to notice that also political uncertainty about future RES-E deployment paths exists. Binding RES-E targets on a European level have only been formulated until 2020. In Germany, RES-E targets until 2050 have been additionally been formulated (Energiekonzept (2010)). Not all other European countries have long-term RES-E strategies yet. In addition, changes of political targets could occur with some probability. These risks are not incorporated in our model calculations.

In this chapter we describe the scenario tree representing uncertainty about the implementation of political RES-E targets (section 5.1) and present model results with regard to investment decisions, electricity generation and system costs (section 5.2).

5.1. Representation of the RES-E implementation risk

In order to represent the RES-E implementation risk in the model we estimate possible bandwidths of RES-E deployments within the next decades based on targeted growth rates indicated in the National Renewable Energy Action Plans (NREAP)[10], on actual trends regarding the achievement of these targets, on possible obstacles to RES-E deployment and on space potential restrictions per technology and country.

The first model year considered in the analysis is 2015, when investment decisions have to be made for power plants commissioning in 2020. The model year 2020 is represented by three nodes, taking into account that the NREAP can be exactly reached but also be surpassed or not be reached. Lower RES-E deployments than targeted represent a case in which slow progresses in grid and plant constructions, local opposition to new power plant construction and/or a lack of funds hinders RES-E deployment. Especially the achievement of wind offshore targets has been questioned recently because of slow progresses in grid and plant constructions. In contrast, higher than targeted RES-E deployments represent a case in which hardly obstacles to plant and grid construction exist and/or cost degressions of RES-E plants are higher than foreseen. Especially photovoltaic targets are easily surpassed in price-based RES-E support systems besides for very low promotion payment levels, because the support of the local population is often high and the space potential is vast.

Table 9 depicts the RES-E capacities in 2010, the foreseen deployment in GW between 2010 and 2020 according to the NREAP and the installed RES-E capacities in 2020 when the NREAP is exactly reached, surpassed or not reached. Historical capacities in 2010 are based on the NREAP documents, Eurelectric (2009) and BMU (2011).

[10] Within the National Renewable Energy Action Plans the Member States of the European Union defined how the national 2020 RES targets according to the 2009 EU Directive on the promotion of renewable energy sources are broken down into targets for the transporting, the heating and cooling and the electricity sector.

Table 9: RES-E capacities in 2010 and 2020 [GW]

Region	Technology	**2010**	**growth NREAP**	**NREAP 2020**	**> NREAP 2020**	**< NREAP 2020**
Germany	wind onshore	27	9	36	40	30
	wind offshore	0	10	10	12	3
	photovoltaics	17	34	52	60	35
	biomass	7	2	9	10	8
	geothermal	0	0	0	1	0
Benelux	wind onshore	3	8	10	12	6
	wind offshore	0	5	5	7	2
	photovoltaics	0	2	2	4	1
	biomass	2	3	5	6	5
	geothermal	0	0	0	0	0
France	wind onshore	6	13	19	25	10
	wind offshore	0	6	6	8	1
	photovoltaics	1	4	5	10	2
	biomass	1	2	3	4	2
	geothermal	0	0	0	0	0
CH + AT	wind onshore	1	2	3	4	2
	wind offshore	0	0	0	0	0
	photovoltaics	0	0	0	1	0
	biomass	1	0	1	2	1
	geothermal	0	0	0	0	0
CZ+ PL	wind onshore	1	5	6	9	3
	wind offshore	0	1	1	1	0
	photovoltaics	2	0	2	2	2
	biomass	0	3	3	4	0
	geothermal	0	0	0	0	0
Denmark	wind onshore	3	0	3	3	3
	wind offshore	1	1	1	2	1
	photovoltaics	0	0	0	0	0
	biomass	1	2	3	4	2
	geothermal	0	0	0	0	0

For the timeframe after 2020, we estimate possible bandwidth for a high or a moderate RES-E deployment pace based on the same considerations. For the case of favorable investment conditions, we assume that the deployment between 2010 and 2020 according to the NREAP is carried forward in the coming decades while in the presence of obstacles to RES-E deployment, the deployment is assumed to be one half of this growth. For offshore wind we deviate slightly from this procedure, because experiences with offshore plants are few and unused space potential in all considered countries is still vast. Thus, for offshore, the deployment at high pace is assumed to be twice the development in the NREAP between 2010 and 2020, while a deployment at moderate pace is assumed to be the same as within the NREAP. In addition, we take into account that (space or fuel) potential restrictions (see Table A.1 in the Appendix) need to be respected and that the maximal yearly RES-E production of all RES-E technologies reaches at most 90% of the annual country-specific electricity demand.

Figure 3 recaptures the resulting structure of the scenario tree representing the RES-E implementation risk for Germany and its neighboring countries. We assume that factors favoring and factors hindering a high RES-E deployment pace are realized with the same probability such that all nodes depicted in Figure 3 have the same occurence probability. Also, with the chosen approach we implicitly assume that different risks associated with the deployment of different RES-E technologies are positively correlated in all model regions.[11] In addition we assume that most uncertainties about technological and cost developments and about grid construction progresses have resolved from 2040 onwards.[12]

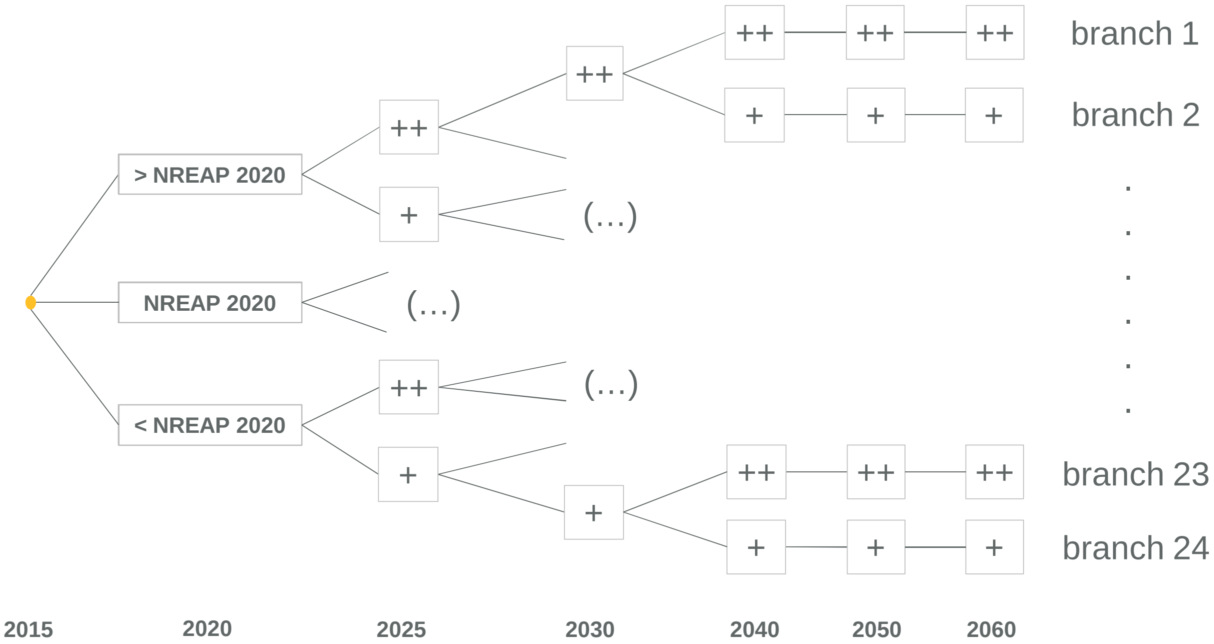

Figure 3: Structure of the scenario tree representing the RES-E implementation risk

Resulting RES-E capacities per node for the model years 2030 and 2050 can be found in the Appendix. For example in Germany in the year 2030, RES-E capacities vary between 109 GW (node $n12$) and 187 GW (node $n1$). In terms of RES-E generation, bandwidths are between 225 TWh and 383 TWh, which make up 37% respectively 63% of the assumed electricity demand in 2030. In 2050 maximum assumed bandwidth

[11] Possible negative correlations could both increase or attenuate the effects of the RES-E implemenation risk. For example a high offshore wind and a high photovoltaic penetration can lead to a less volatile residual load than a high penetration of both technologies. Thus, including paths with high offshore and low photovoltaic penetrations may even increase the possible bandwith of residual load curves captured in the scenario tree and increase effects of uncertainty. On the other hand, including paths with high offshore and low onshore wind penetrations and vice versa may lead to increasing probabilities for these "medium" paths such that effects of uncertainty diminish to some extent.

[12] In our analysis we focus on investments decisions until 2020 and corresponding dispatch decisions until 2025. In order to include effects of long-term uncertainties on investment decisions with long amortization and lifetimes, we however include nodes until 2060. Overall, the chosen scenario tree consists of 24 branches and 94 nodes.

for Germany are between 141 GW (node $n24$) and 244 GW (node $n1$), resulting in RES-E shares of 47% respectively 78% with our assumed demand development.[13]

5.2. Model results

In the following we analyze the effects of the RES-E implementation risk on investment and dispatch decisions (section 5.2.1) as well as on system costs (section 5.2.2).

5.2.1. Effects of RES-E implementation risks on investment and dispatch decisions

Table 10 depicts investment decisions made in 2015 within all modeled countries. Within branch 1, characterized by the highest possible RES-E penetration in all model years (NREAP surpassed in 2020 and fast pace growth in each following period), only lignite and OCGT plants are constructed. In branch 24 with the lowest possible RES-E generation, also coal and CCGT plants are chosen. Lignite investments are identical in all branches, because lignite generation is characterized by very low variable costs and is in addition restricted to local fuel potentials. Note that nuclear is not an investment option in the first model year.

Table 10: Investments in 2015 in all model regions [GW]

	Branch 1 (max RES-E)	Branch 24 (min RES-E)	stochastic	average of all det branches
Lignite	3	3	3	3
Coal		10		2
CCGT		3	3	2
OCGT	18	12	23	18
CHP-Coal				
CHP-Gas				
Nuclear				
Storage				
sum	21	28	29	25

Under uncertainty, no investments into coal plants take place. In contrast, CCGT and especially OCGT investments are higher than on average under certainty. The result of lower coal and higher CCGT investments reflects the effect discussed in the illustrative modeling example (Section 4): As coal is only cost-efficient in some scenarios, investments with lower capital/operating cost ratios are chosen under uncertainty in order to hedge against the risk of high investment expenditures for plants which might only run for few hours. In contrast, higher OCGT investments under uncertainty are only cost-efficient because of an

[13]For Germany an estimation about possible bandwidth of RES-E generation in a 5-year-period can also be found in the medium-term RES-E generation forecast (IE Leipzig (2011)). As a lower bound for promoted RES-E generation in 2016, about 130 TWh are indicated, as a higher bound about 210 TWh. Although this bandwidth is based both on possible ranges for RES-E deployment and for different wind and water infeed assumptions, it clearly confirms that even within a short time horizon, RES-E developments can be quite uncertain.

existing power plant fleet. In the illustrative modelling example lower OCGT investments are chosen under uncertainty, because a high utilization of these capacities in the case of a low RES-E penetration would induce high costs. Due to the existing power plant fleet of the Central European power market which is now taken into account, the additional OCGT capacities built under uncertainty are not needed to meet demand in 2020. Even in the scenario with the lowest RES-E penetration (branch 24), demand can be met by a different dispatch of existing power plants such that the additional OCGT plants built under uncertainty only serve as backup capacities in all scenarios. Specifically, the utilization of existing CCGT plants in branch 24 is higher under uncertainty. In addition, generation in lignite-CHP plants is reduced such that generation in non-CHP lignite plants can be increased (- due to the lignite fuel bound only a limited amount of lignite can be used per year). CHP generation from lignite plants is replaced by a higher utilization of gas and coal CHP plants. In addition, the utilization of pump storage plants is higher than under certainty such that the utilization of existing baseload plants can be increased compared to the deterministic case, when more investments into baseload plants are made in 2015. In branch 1, characterized by the highest RES-E penetration, the different optimal investment plan under uncertainty leads to a higher amount of total installed capacities and to a larger share of CCGT capacities in 2020. Consequently, a larger share of demand in 2020 is met by CCGT plants instead of old coal plants which have higher variable costs than new built CCGT plants due to low efficiency values.

These generation differences are recaptured in Figure 4. Interestingly, although in branch 1 and 24 uncertainty leads to a replacement of coal by CCGT generation, this generation difference leads to lower variable costs in branch 1 compared to the deterministic case while variable costs in branch 24 are comparatively higher. While in branch 1 CCGT generation replaces coal generation in old existing coal plants, differences in branch 24 occur because new efficient coal plants built in the deterministic case, are not available under uncertainty.

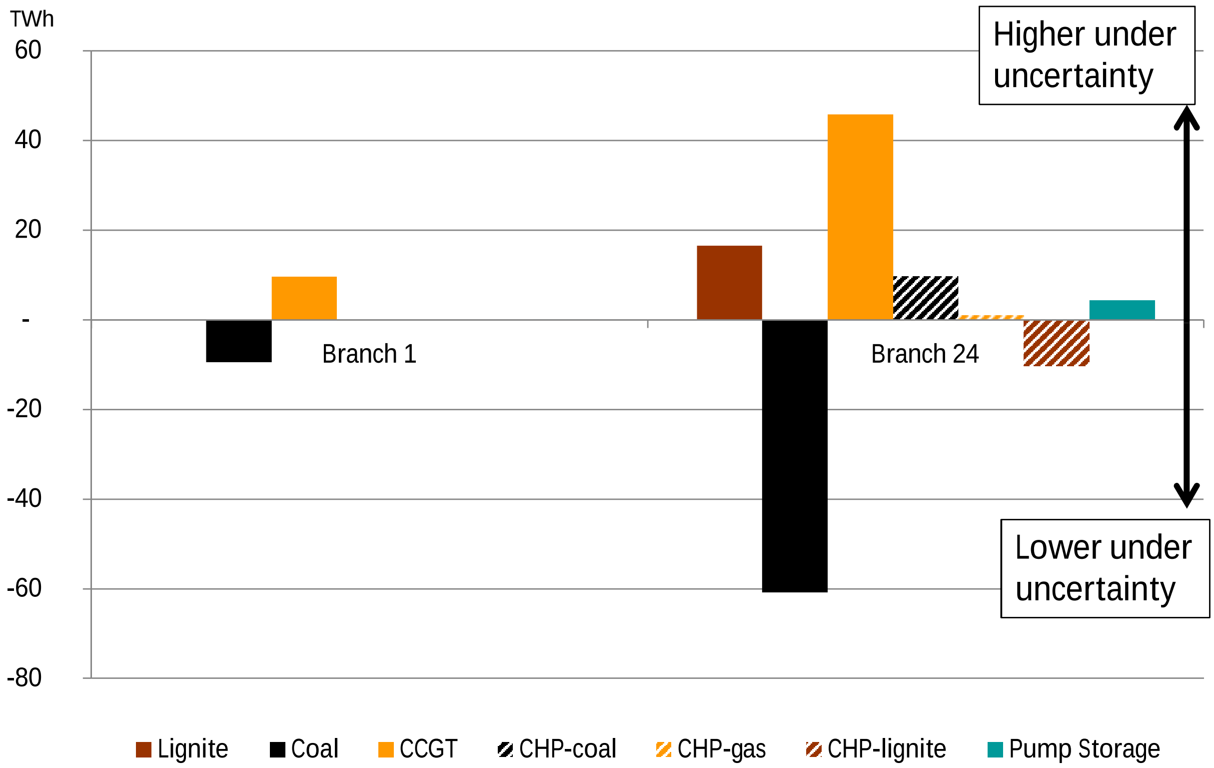

Figure 4: Generation differences in 2020 between deterministic and stochastic case [TWh]

Investment choices in 2020 between the stochastic and the deterministic solutions differ mainly because the power plant fleet in the stochastic approach is adapted to newly available information about future RES-E deployments. Table 11 depicts investment decisions made without uncertainty in branches 1 and 24 as well as the average values for all eight deterministic branches passing through node n1 respectively node n3 and the stochastic values for nodes n1 and n3. Nuclear investments are identical in all deterministic and stochastic cases because generation costs are comparatively low and investments are restricted (see Section 3). Lignite investments are also identical in all branches passing through the same 2020 node such that investments into lignite plants are not subject to uncertainty.

Table 11: Investments in 2020 in all model regions [GW]

	Branch 1	av (n1)	stoch (n1)	Branch 24	av (n3)	stoch (n3)
Lignite	7	7	7	10	10	10
Coal						
CCGT	13	17	13	35	31	42
OCGT	34	31	28	15	17	8
CHP-Coal						
CHP-Gas						
Nuclear	6	6	6	6	6	6
Storage						
sum	60	61	54	66	64	66

Considering node n1 (characterized by a surpassed NREAP), it can be seen that under certainty less investments into CCGT and OCGT plants are made compared to the average investments in the deterministic scenario calculations. Lower investments are cost-efficient, because under uncertainty more CCGT and OCGT plants have been constructed in the period before 2020. Considering branch 1, CCGT investments in 2020 are identical in the stochastic and deterministic case. Thus, due to the higher CCGT investments in 2015 under uncertainty, installed CCGT capacities in 2025 are higher than in the deterministic case. Consequently, resulting dispatch decisions (branch 1) in 2025 hardly differ from those in 2020. Under uncertainty, a larger part of demand is met by CCGT plants while generation from coal plants is lower than under certainty.

Node n3 (low RES-E share) is characterized by substantially larger CCGT investments under uncertainty. OCGT investments are in contrast lower than in the deterministic case. Additional CCGT capacities are built in order to catch-up lower base- and midload plant investments (coal and CCGT) made in 2015. CCGT rather than coal plants are chosen to catch-up lower baseload investments because increasing CO_2 prices and RES-E shares over time lead to an increasing relative value of CCGT plants compared to coal plants. Fewer investments into OCGT plants are cost-efficient under uncertainty in 2020, because the capacity mix already comprises larger OCGT-shares than under certainty due the 2015 investments. Resulting dispatch decisions (branch 24) in 2025 are again characterized by a higher CCGT and pump storage generation and by a lower coal generation than under certainty. Results for later model years generally reflect the same effects and are thus not discussed in more detail.

5.2.2. Effects of RES-E implementation risks on system costs

Figure 5 depicts additional capital costs, additional variable costs and additional total costs arising in each of the 24 branches due to the uncertainty about the magnitude and the pace of future RES-E deployments in Germany and its neighboring countries. Depicted costs are discounted with a 5 % rate and accumulated until 2060. In branches with high RES-E shares, such as branch 1, investment planning under uncertainty induces additional capital costs (+ 9 bn €$_{2010}$ until 2060 in branch 1) because many mid- and baseload plants built under uncertainty are not cost-efficient for these branches. However, variable generation costs decrease due to the availability of generation options with low variable costs (- 4 bn €$_{2010}$). In contrast, in branches with low RES-E shares, such as branch 24, additional variable costs are high (+ 11 bn €$_{2010}$ until 2060 in branch 24) while capital costs are lower than in the deterministic case (- 9 bn €$_{2010}$).

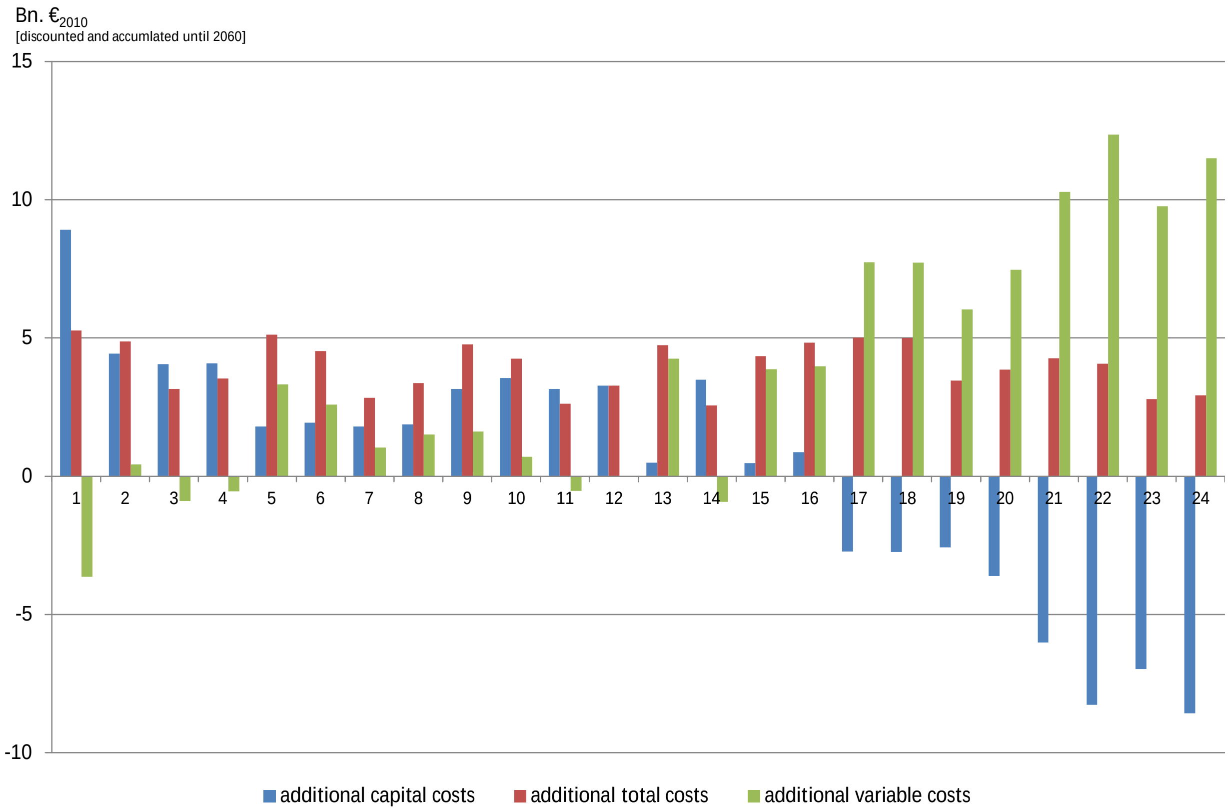

Figure 5: Additional costs induced by the RES-E implementation risk (per branch) [bn €$_{2010}$]

Total additional costs induced by uncertainty amount to 4 bn €$_{2010}$ on average. Compared to total average deterministic costs, these costs however represent only 0.3%. One reason is, that investment requirements are low in those periods, when uncertainty is highest.[14] Investment decisions are exposed most to uncertainty in 2015 when RES-E penetrations until 2060 are unknown. Besides exogenous commissions of power plants which are already in the construction process today, investment requirements to meet demand

[14]In a quite different context, Manne (1974) finds that the expected value of perfect information about the date nuclear breeder technology becomes available is very low (0.04% of average deterministic costs), because decisions can be defererred to periods when uncertainty is at least partly resolved. Sufficient old power plants require only few investments in the period, when uncertainty is highest.

in 2020 are low. Endogenous investment decisions in 2015 amount to between 21 and 29 GW - representing approximately 7% of total installed capacities. In addition, due to an existing power plant fleet, not all of the new investments are necessarily needed to meet demand. For example in branch 24, stochastic investment planning in 2015 does not lead to a higher OCGT generation in 2020 although from a capacity point of view, some of the OCGT plants replace coal plants, built under certainty. Thus, the existing power plant permits to postpone some investment decisions to a period when more information is available. Another reason for low additional costs is that not all capacity investments are exposed to risk. Lignite and nuclear plants are built in all paths nearly (lignite) respectively exactly (nuclear) to the same amount. Both technologies have low variable costs and are in addition restricted by natural resource or political constraints.

6. Conclusions

Uncertainty about future RES-E deployment paths leads to uncertainty about the level and the slope of the residual load which needs to be met by dispatchable power plants and storage units. We find that plants with a medium capital/operating cost ratio and medium flexibility characteristics in terms of ramping times, minimum load constraints and part load efficiency losses, are cost-efficiently deployed under uncertainty about future developments of the residual load. In addition, investment decisions for capital-intensive plants are postponed under uncertainty. Furthermore we have shown that the value of storage units in electricity systems with high RES-E penetrations decreases, because investment planning under uncertainty leads to a flatter merit-order curve compared to the the case of perfect foresight about high RES-E penetrations. The impact on system costs however is rather small if we assume that a long-term increase of the RES-E share is reliable and that only the magnitude and the pace of the increase are uncertain.

Based on our analysis, the following implications can be drawn for optimal investment planning and policy. Firstly, it is important to take into account possible implementation risks associated with RES-E targets because a different technology choice or a different point of time might be beneficial for the investment. Secondly, many old power plants whose decommissioning might seem cost-efficient based on deterministic optimization models are valuable under uncertainty. Thirdly, reliable long-term political targets are crucial in order to limit uncertainty. Fourthly, the effects of RES-E implementation risks need to be considered in the ongoing debate about the necessity of capacity payments in the context of an increasing RES-E share. From deterministic model calculations it is known that with an increasing RES-E share, a large amount of backup capacities is needed, which however only run for very few hours. The capacity payment debate focuses on the question whether investment incentives for these plants are high enough without additional payments. Our analysis shows that under uncertainty about the pace of future RES-E deployments, power plants are needed which are only dispatched if RES-E deployment plans progress slowly. We analyze the effects of RES-E implementation risks from the perspective of a risk-neutral central planner, who recovers all costs on average. However, in some scenarios electricity prices are not sufficient to cover investment expenditures. Whether risk-averse investors would invest within this uncertain environment without additional incentives, is an interesting area of further research. Also, we have focused on only one source of uncertainty associated with the envisaged transformation process towards a low-carbon and mainly renewable based European electricity system. However, this transformation process relies on three pillars: An increasing share of renewable energy, increasing energy efficiency and a reduction of CO_2 emissions. In this context, future CO_2 prices and the progress of energy efficiency measures are additional sources of uncertainty about the optimal capacity mix of conventional power plants and storage units. A combined analysis of these uncertainties provides an interesting area of further research and would contribute to a better understanding of optimal power plant investment planning within the context of the envisaged transformation process.

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Appendix

Table A.1: Assumed potential restrictions

Technology	Germany	Benelux	France	CH + AT	CZ + PL	Denmark
Wind Onshore [km^2]	2174	497	3215	252	2429	300
Wind Offshore [km^2]	7200	11054	4050	-	1410	8520
Biomass [TWh_{th}]	177	44	356	42	141	34

Table A.2: RES-E capacities in 2030 [GW]

Region	Technology	n1	n2	n3	n4	n5	n6	n7	n8	n9	n10	n11	n12
Germany	wind onshore	48.5	46.4	46.4	44.3	44.3	42.2	42.2	40.0	38.5	36.4	36.4	34.3
	wind offshore	31.7	26.8	26.8	21.9	29.7	24.8	24.8	19.9	22.7	17.8	17.8	12.9
	photovoltaics	94.4	85.8	85.8	77.2	86.2	77.6	77.6	69.0	69.4	60.8	60.8	52.2
	biomass	11.7	11.2	11.2	10.6	11.0	10.5	10.5	9.9	10.2	9.7	9.7	9.1
	geothermal	0.8	0.7	0.7	0.6	0.6	0.5	0.5	0.4	0.3	0.2	0.2	0.2
Benelux	wind onshore	15.0	15.0	15.0	15.0	15.0	15.0	15.0	14.0	13.5	11.7	11.7	9.8
	wind offshore	17.2	14.7	14.7	12.1	15.6	13.0	13.0	10.5	12.2	9.7	9.7	7.1
	photovoltaics	5.7	5.3	5.3	4.9	3.9	3.5	3.5	3.0	2.7	2.3	2.3	1.9
	biomass	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0
	geothermal	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
France	wind onshore	38.5	35.1	35.1	31.7	32.5	29.1	29.1	25.7	23.5	20.1	20.1	16.7
	wind offshore	20.0	17.0	17.0	14.0	18.0	15.0	15.0	12.0	13.0	10.0	10.0	7.0
	photovoltaics	14.4	13.3	13.3	12.2	9.2	8.1	8.1	7.0	6.4	5.3	5.3	4.2
	biomass	6.0	5.5	5.5	5.0	5.0	4.5	4.5	4.0	4.0	3.5	3.5	3.0
	geothermal	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.0	0.0	0.0
CH + AT	wind onshore	5.6	5.2	5.2	4.8	4.2	3.8	3.8	3.4	3.6	3.2	3.2	2.8
	wind offshore	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	photovoltaics	1.2	1.2	1.2	1.1	0.6	0.6	0.6	0.5	0.5	0.5	0.5	0.4
	biomass	3.3	3.0	3.0	2.6	2.6	2.2	2.2	1.9	2.3	2.0	2.0	1.6
	geothermal	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
CZ+ PL	wind onshore	14.0	12.8	12.8	11.5	11.3	10.1	10.1	8.8	8.0	6.8	6.8	5.5
	wind offshore	2.0	1.8	1.8	1.5	1.5	1.3	1.3	1.0	1.0	0.8	0.8	0.5
	photovoltaics	2.0	2.0	2.0	2.0	1.7	1.7	1.7	1.7	1.7	1.7	1.7	1.7
	biomass	6.3	5.6	5.6	4.9	5.8	5.1	5.1	4.4	3.1	2.4	2.4	1.7
	geothermal	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Denmark	wind onshore	2.7	2.8	2.8	2.8	2.3	2.4	2.4	2.5	2.3	2.4	2.4	2.5
	wind offshore	2.3	2.3	2.3	2.2	1.7	1.6	1.6	1.5	1.3	1.3	1.3	1.2
	photovoltaics	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	biomass	3.9	3.8	3.8	3.7	3.2	3.1	3.1	3.0	1.9	1.8	1.8	1.7
	geothermal	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Table A.3: RES-E capacities in 2050 [GW]

Region	Technology	n1	n2	n3	n4	n5	n6	n7	n8	n9	n10	n11	n12	n13	n14	n15	n16	n17	n18	n19	n20	n21	n22	n23	n24
Germany	wind onshore	50.0	50.0	50.0	50.0	50.0	50.0	50.0	48.5	50.0	48.6	50.0	46.4	50.0	46.4	48.6	44.3	47.1	42.8	45.0	40.7	45.0	40.7	42.8	38.5
	wind offshore	50.0	41.6	46.5	36.6	46.5	36.6	41.6	31.7	49.4	39.6	44.5	34.6	44.5	34.6	39.6	29.7	42.4	32.6	37.5	27.6	37.5	27.6	32.6	22.7
	photovoltaics	128.9	111.6	120.3	103.0	120.3	103.0	111.6	94.4	120.6	103.4	112.0	94.8	112.0	94.8	103.4	86.2	103.9	86.6	95.3	78.0	95.3	78.0	86.6	69.4
	biomass	13.9	12.8	13.4	12.3	13.4	12.3	12.8	11.7	13.3	12.1	12.7	11.6	12.7	11.6	12.1	11.0	12.4	11.3	11.9	10.8	11.9	10.8	11.3	10.2
	geothermal	1.1	0.9	1.0	0.9	1.0	0.9	0.9	0.8	0.9	0.7	0.8	0.7	0.8	0.7	0.7	0.6	0.6	0.4	0.5	0.4	0.5	0.4	0.4	0.3
Benelux	wind onshore	15.0	15.0	15.0	15.0	15.0	15.0	15.0	15.0	15.0	15.0	15.0	15.0	15.0	15.0	15.0	15.0	15.0	15.0	15.0	15.0	15.0	15.0	15.0	13.5
	wind offshore	27.4	22.3	24.9	19.8	24.9	19.8	22.3	17.2	25.8	20.7	23.2	18.1	23.2	18.1	20.7	15.6	22.4	17.3	19.9	14.8	19.9	14.8	17.3	12.2
	photovoltaics	7.4	6.6	7.0	6.1	7.0	6.1	6.6	5.7	5.6	4.7	5.2	4.3	5.2	4.3	4.7	3.9	4.4	3.6	4.0	3.1	4.0	3.1	3.6	2.7
	biomass	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0	6.0
	geothermal	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
France	wind onshore	51.9	45.2	48.6	41.8	48.6	41.8	45.2	38.5	45.9	39.2	42.6	35.8	42.6	35.8	39.2	32.5	36.9	30.2	33.6	26.8	33.6	26.8	30.2	23.5
	wind offshore	30.0	26.0	29.0	23.0	29.0	23.0	26.0	20.0	30.0	24.0	27.0	21.0	27.0	21.0	24.0	18.0	25.0	19.0	22.0	16.0	22.0	16.0	19.0	13.0
	photovoltaics	18.7	16.5	17.6	15.4	17.6	15.4	16.5	14.4	13.6	11.4	12.5	10.3	12.5	10.3	11.4	9.2	10.7	8.5	9.6	7.4	9.6	7.4	8.5	6.4
	biomass	7.9	6.9	7.4	6.4	7.4	6.4	6.9	6.0	6.9	5.9	6.4	5.5	6.4	5.5	5.9	5.0	5.9	4.9	5.4	4.4	5.4	4.4	4.9	4.0
	geothermal	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
CH + AT	wind onshore	6.0	6.0	6.0	6.0	6.0	6.0	6.0	5.6	5.7	4.9	5.3	4.6	5.3	4.6	4.9	4.2	5.1	4.4	4.7	4.0	4.7	4.0	4.4	3.6
	wind offshore	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	photovoltaics	1.5	1.3	1.4	1.3	1.4	1.3	1.3	1.2	0.9	0.7	0.8	0.7	0.8	0.7	0.7	0.6	0.8	0.6	0.7	0.6	0.7	0.6	0.6	0.5
	biomass	4.6	3.9	4.2	3.6	4.2	3.6	3.9	3.3	3.8	3.2	3.5	2.9	3.5	2.9	3.2	2.6	3.6	2.9	3.2	2.6	3.2	2.6	2.9	2.3
	geothermal	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
CZ+ PL	wind onshore	19.0	16.5	17.8	15.3	17.8	15.3	16.5	14.0	16.3	13.8	15.1	12.6	15.1	12.6	13.8	11.3	13.0	10.5	11.8	9.3	11.8	9.3	10.5	8.0
	wind offshore	3.0	2.5	2.8	2.3	2.8	2.3	2.5	2.0	2.5	2.0	2.3	1.8	2.3	1.8	2.0	1.5	2.0	1.5	1.8	1.3	1.8	1.3	1.5	1.0
	photovoltaics	2.1	2.1	2.1	2.1	2.1	2.1	2.1	2.0	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.7	1.8	1.8	1.8	1.8	1.8	1.8	1.8	1.7
	biomass	9.2	7.8	8.5	7.0	8.5	7.0	7.8	6.3	8.6	7.2	7.9	6.5	7.9	6.5	7.2	5.8	6.0	4.6	5.3	3.8	5.3	3.8	4.6	3.1
	geothermal	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Denmark	wind onshore	2.4	2.5	2.5	2.6	2.5	2.6	2.5	2.7	2.0	2.2	2.1	2.2	2.1	2.2	2.2	2.3	2.0	2.2	2.1	2.2	2.1	2.2	2.2	2.3
	wind offshore	2.6	2.5	2.5	2.4	2.5	2.4	2.4	2.3	1.9	1.8	1.8	1.7	1.8	1.7	1.8	1.6	1.6	1.5	1.5	1.4	1.5	1.4	1.4	1.3
	photovoltaics	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	biomass	4.2	4.1	4.1	3.9	4.1	3.9	3.9	3.8	3.4	3.3	3.3	3.2	3.3	3.2	3.2	3.1	2.2	2.1	2.1	1.9	2.1	1.9	1.9	1.8
	geothermal	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0