Business case uncertainty of power plants in future energy systems with wind power

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HIGHLIGHTS

- The operation of thermal power plants is affected by CO₂ prices and wind power.
- A new tool quantifies the effect of their uncertainty on power plant profitability.
- New power plants are unprofitable and show a large spread in expected profits.
- Uncertain future climate policy is a key factor in all business cases ($\pm 56\%$ change).
- Increasing wind power penetration (10–21%) decreases profitability by 14%.

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ABSTRACT

The European power sector is transforming due to climate policies and an increased deployment of intermittent RES. The sector will require thermal power plants for the decades to come, but their business cases are (negatively) affected by this transformation. This study presents a novel tool to quantify the effect of policy, price and project-related uncertainties on power plant business cases. This tool can support policymakers in stimulating necessary investments in new thermal generation capacity. We find that these investments are currently unsound (power plants recoup on average -12% to 59% of their initial investment). Future climate policy, i.e. the CO₂ price, has a very strong impact on business cases (affects the profitability by $5\text{--}40\%$ -points). The impact of the deployment of wind power is average ($2\text{--}8\%$ -point difference between 10% and 21% wind penetration). Variations in annual wind power production barely affect the profitability (variation of $\pm 1\%$ -point). To stimulate new investments, policymakers should first decrease the uncertainty in business cases caused by policy. Durable climate policy is especially important. Also, policies to increase the profits of thermal power plants should be carefully considered and implemented. This combined approach will reduce the revenue gap that needs to be bridged by supportive policies.

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Abbreviations: CCS, Carbon capture and storage; EU, European union; FO&M, Fixed operation and maintenance; GIS, Geographic information system; GT, Gas turbine; IDC, Interest during construction; IEA, International energy agency; iRES, Intermittent renewable energy sources; LCOE, Levelized cost of electricity; LP, Linear programming; MIP, Mixed integer programming; NG, Natural gas; NGCC, Natural gas combined cycle; NGCC-CCS, Natural gas combined cycle with CCS; NL, The Netherlands; NPV, Net present value; PI, Profitability index; PC, Pulverized coal; PC-CCS, Pulverized coal with CCS; TCR, Total capital requirement; TOC, Total overnight costs; UCED, Unit commitment and economic dispatch; VO&M, Variable operation and maintenance

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1. Introduction

The European power sector has changed significantly in the past 20 years as a result of liberalization, increased privatization, introduction of climate policies and deployment of renewable sources (OECD/IEA, 2014a; Verbong and Geels, 2007). The sector will continue to evolve, important changes being more stringent climate policies and capacity expansions of intermittent renewable energy sources (iRES, i.e. wind and solar PV). These expansions are driven by climate policies, cost reductions and energy security reasons (EC, 2011a; OECD/IEA, 2014a).

In addition to iRES, thermal power plants will still be needed to ensure affordable and reliable electricity for the decades to come

(Brouwer et al., 2016; OECD/IEA, 2014b). The role of thermal power plants in future power systems may change, as climate policies and increased iRES deployment affect power system operations by changing the merit order and residual load patterns. In their new role, power plants may have different capacity factors, they may have to operate more flexibly and they may receive different prices for their generated electricity. The uncertainty in these new developments adds to the risk that investors are exposed to (price risks and volume risks), and hence increases the uncertainty in their business cases (Finon, 2011). As investments must be profitable under a sufficiently wide range of future developments, this increased uncertainty discourages new investments in thermal power plants. In fact, the business cases for new thermal power plants are unsound right now, resulting in new power plants being dismantled rather than being built (Parkinson, 2015).

Nevertheless, estimated investments of 170 billion Euros in thermal power plants are needed to replace the aging generator stock in Europe from 2014 to 2035 (OECD/IEA, 2014a). In light of the uncertain business cases of thermal power plants, policymakers need to understand how these business cases are affected by uncertainty in important factors such as policies, fuel prices and iRES deployment. This will enable them to design effective policies to stimulate investments – potentially by generating additional revenues to bridge their revenue gap (BMWi, 2014; DECC, 2011).

Quantifying the effect of uncertain input parameters on the expected outcomes requires a stochastic approach, rather than a deterministic approach, the latter of which has been used in the past to quantify thermal power plant business cases (e.g. Bertsch et al., 2012; Brouwer et al., 2015, 2016; Stienstra et al., 2010). A stochastic approach can account for uncertainty in input parameters, which is caused by their stochastic nature (i.e. iRES-parameters) or imperfect information (e.g. future climate policy). Moreover, it calculates a range of outcomes, along with their probabilities. Policymakers can evaluate the robustness of future policies with this information (e.g. policies that ensure profitability in a range of future developments) (Becker et al., 1994).

The business cases of new power plants have been stochastically appraised in previous studies at (1) a power plant level and (2) a power system level. The first group of stochastic studies aimed to maximize the net present value (NPV) of power plants with uncertain input parameters. These studies included stochastic fuel prices, in addition to stochastic electricity prices (He, 2010; Rohlf and Madlener, 2014), capacity factors (Roques, 2007), or CO₂ prices (Yang et al., 2008). They evaluated a power plant business case over the course of its lifetime, often including endogenous decisions to upgrade or mothball the generator. Four other studies aimed to identify generation portfolios with both low costs and low uncertainty using a Monte-Carlo tool. Vithayasrichareon and MacGill (2013, 2012) presented a tool to quantify the cost distribution of new generation portfolios, whilst accounting for uncertain fuel and CO₂ prices as well as investment costs. Bhattacharya and Kojima (2012) calculated generation mixed for Japan by minimizing both total system costs and system uncertainty. Roques et al. (2006) calculated the NPV distribution of mixed portfolios that contain generators with complementary risk-return profiles. The strong point of this group studies is that they stochastically calculate the profitability of power plants considering a range of uncertain input parameters. However, neither the generator-focused nor the portfolio-focused studies endogenously calculated the capacity factor and electricity prices, which are vital parameters for power plant business case calculations.

A second group of stochastic studies focused on power system operation. Hart and Jacobson (2011) presented a Monte-Carlo model that performs basic power system simulations, and which is especially suited for planning generation portfolios with high

shares of iRES. The model accounts for variability and unpredictability of iRES, and ensures a predefined power system reliability. Due to its long-term focus, dispatch simulations are simplified by including only 7 aggregated generators and limiting the temporal scope to 28 days a year. This makes this model less suitable for business case analyses. Lastly, two stochastic power system studies quantified system operation (Meibom et al., 2008) and power plant dispatch (Tuohy et al., 2009), whilst accounting for uncertain iRES production forecasts and generator outages. The strong point of these studies is that they simulate power system operation, and hence endogenously calculate the electricity prices and capacity factors of power plants. Moreover, they can endogenously simulate the impact of iRES on the power system and its generators. None of these three studies quantified the business cases of power plants, though.

This study introduces a novel approach that combines the strong points of both groups of stochastic studies. It utilizes a soft-linked power system simulation tool and a Monte-Carlo business case analysis tool. The former tool endogenously simulates the effect of uncertain input parameters that affect the whole power system, such as wind penetration and CO₂ prices. Its output is fed into the latter tool, which performs a stochastic business case analysis that accounts for uncertain input parameters that affect individual power plants. Its output is a distribution of the expected profits of thermal power plants in the current energy-only market. We use this approach to answer the main research question: *how are the business cases of thermal generators built in 2020 in Europe affected by uncertainties around wind power and climate policy?* As such, this approach can give policymakers insight in the driving factors behind investment decisions and aid policy design.

The focus of this study is on uncertainties in wind power because it is projected to stay the largest type of intermittent renewable generation in Europe until at least 2050 (GEA, 2012; OECD/IEA, 2014c). Specifically, we focus on the uncertainties related to the level of wind penetration and to the annual variation in wind power generation to limit the scope of the study.¹

The original contribution of this paper is threefold:

1. A new approach in which a unit commitment and economic dispatch (UCED) tool and a Monte-Carlo business case analysis tool are soft-linked.
2. We use this new approach to calculate the expected distribution of the profitability index (PI) of generators built in the year 2020 in the current energy-only market.
3. We quantify the effect of uncertainty in climate policies as well as uncertainty in wind power penetration and annual wind power production on the PI of generators.

The layout of the paper includes the method (Section 2), and key input data (Section 3). Next, the results (Section 4), discussion (Section 5) and conclusion (Section 6) are presented.

2. Method

2.1. Overview

We soft-link the COMPETES UCED tool and a Monte-Carlo business case tool to calculate the distribution of the Profitability Index (PI, see Eq. (1)) of five types of thermal power plants. We

¹ The distribution of iRES is a third uncertainty in addition to the penetration and annual variation, which could affect the power system. Investigating distribution-uncertainties would require reliability calculations to determine the iRES capacity credit, and a higher geographic resolution than the UCED model currently does not possess.

Table 1
Overview of scenarios and cases simulated with the COMPETES tool.

Scenarios/cases	Letter		Average						
Climate policy scenarios	C	Business as usual	C1	C2	C3	C4	C5	Strict policies	
Wind penetration scenarios	P	Low	P1	P2	P3	P4	P5	High	
NG:coal price ratio ^a cases	G	penetration	G1	G2	G3	G4	G5	penetration	
Wind year cases	Y	Low ratio	Y1	Y2	Y3	Y4	Y5	High ratio	
		Low wind availability						High wind availability	

^a A low ratio results in relatively low natural gas prices, and a high ratio in relatively high natural gas prices.

Table 2
Uncertain and fixed input parameters used in the COMPETES and Monte-Carlo tools.

	COMPETES tool ^a		Monte-Carlo tool	
System uncertainties	Uncertain input	Fixed input	Uncertain input	Fixed input
Climate policy (CO ₂ and coal price) (€/tCO ₂ , €/GJ)	■		■	
Wind penetration (%)	■		■	
NG:coal price ratio (%)	■		■	
Annual wind availability (%)	■		■	
Generator uncertainties			■	
Investment cost (€/kW)		■	■	
Construction time (yr)		■	■	
Fixed O&M cost (€/kW/yr)		■	■	
Variable O&M cost (€/MWh)		■	■	
Lifetime (yr)		■	■	
Short-run profit (€/yr)			o	
Capacity factor (%)			o	
Discount rate (%)				■
CO ₂ capture efficiency penalty (%)		■		
CO ₂ transport and storage costs (€/tCO ₂)		■		
Power plant outages		■		
Efficiency (% LHV)		■		
Minimum load (% of full load)		■		
Ramp rate (% of full load/min)		■		
Start-up costs (€/start/MW)		■		
Financing structure ^b				■

Legend: ■ direct input; o indirect input, calculated by COMPETES and used in the Monte-Carlo tool.

^a Additional fixed inputs are used in the COMPETES model – see Appendix A for a full list.

^b For the purpose of this study, the PI-generators are assumed to be fully financed with equity.

assume these power plants will go online in the year 2020. Next, further capacity additions to the power system between 2020 and 2030 are optimized with COMPETES for 25 scenarios with varying climate policies and wind penetrations. The resulting 25 power systems are simulated in detail with the COMPETES tool for the year 2030 to quantify the operation and profits of the five power plants. Four factors are varied in these simulations to quantify the effect of uncertainty in: (1) climate policy scenarios; (2) wind penetration scenarios²; (3) the availability of wind in each year (“wind years”); and (4) the natural gas:coal (NG:coal) price ratio

(Table 1). The simulated profits per power plant are fitted on regression curves to express them as a continuous function of the wind years and the NG:coal price ratios. These functions are fed into the Monte-Carlo tool, which calculates the distribution of PIs whilst considering seven additional uncertainties (see Table 2 for an overview of uncertain and fixed inputs).

$$\text{Profitability index}_{\text{PI-generator}} = \frac{\text{Present value of future cashflows}_{\text{PI-generator}}}{\text{Initial investment}_{\text{PI-generator}}} \quad (1)$$

The Profitability Index (PI) of a power plant needs to be 100% to break even. The discounted fixed and variable costs of a power plant are equal to the discounted revenue at a PI of 100%. A PI of < 100% means that the power plant will run at a loss, while a PI > 100% shows that the project will make a profit.

The five types of power plants are: Pulverized Coal with and without CCS (PC, PC-CCS), Natural Gas Combined Cycle with and without CCS (NGCC, NGCC-CCS) and Gas Turbines (GT). We focus on a single unit of each of these plants, called the “PI-generators”, which all start operation in 2020 in The Netherlands. This country has been chosen because of the high potential for wind energy in the region, and its good interconnections with neighboring countries. Please note that other types power plants are included in the COMPETES tool, but that they are not further analyzed in the Monte-Carlo tool. These include nuclear, biomass-fired and combined heat and power (CHP) power plants, as shown in Table A.2.

2.2. COMPETES tool

COMPETES is a European electricity market tool developed by ECN. It can perform chronological hourly simulations with either linear programming (LP) or mixed integer programming (MIP) optimization, as well as chronological optimization of capacity additions. All three types of optimizations minimize the sum of the generation cost, load-shedding cost, and, if applicable, amortized costs of capacity expansions (Özdemir et al., 2013b). A detailed description of COMPETES is provided in Appendix A.

COMPETES is used for three reasons: (1) it simulates our region of focus, The Netherlands, with a high level of detail, accounting for individual units and combined heat and power operation; (2) it has the right scope (Europe) and flexibility constraints relevant for assessing the impacts of wind power; (3) the tool and its input dataset have been validated and used in previous studies (Hekkenberg and Verdonk, 2014; Hout et al., 2014; Özdemir et al., 2015a, 2013b).

2.3. Monte-Carlo tool

A Monte-Carlo tool was set up in Microsoft Excel with the @RISK risk analysis add-in.³ This tool is based on the elaborate “Power Systems Financial Model v. 6.6” by NETL (Worhach, 2011). We simplified this model by only considering the key input parameters⁴ as identified by the NPV analyses of Roques et al. (Roques, 2007; Roques et al., 2006). This simplification makes it easier to interpret results and it reduces the computation time of

³ @RISK is a risk assessment add-in for Microsoft Excel. It uses Monte-Carlo analysis to explore the full range of possible outcomes based on predefined distributions of input parameters (Palisade, 2015).

⁴ Roques et al. identified eleven factors with the strongest effect on the NPV of power plants (printed in italics). The *investment cost*, *fixed O&M cost*, *variable O&M cost*, *construction time* and *plant lifetime* are directly included in the Monte-Carlo tool. The *electricity prices* and *capacity factors* are calculated with the COMPETES tool and incorporated in the profit. *CO₂* and *fuel prices* are varied through the climate scenario and NG:coal price ratio case. The *efficiency* and *discount rate* are assumed to be known when the investment decision is made, so these are fixed.

² Solar PV power generation may have comparable effects on thermal generators as wind power. To limit the scope of this study, only wind power is used to demonstrate the modeling framework.

Fig. 1. Schematic overview of study method.

the soft-linked COMPETES and Monte-Carlo approach.⁵ An overview of the input parameters is provided in Table 2.

The Monte-Carlo tool is run with 10,000 iterations using Latin hypercube sampling for each generator. Per iteration, the costs and benefits of each PI-generator are calculated for its total lifetime. The climate and wind penetration scenarios are kept constant per iteration, while the NG:coal price ratio case and wind availability case are randomly picked for each individual year. In the first years the power plant is constructed, resulting in a negative cash flow. Once constructed, the power plant will make annual profits as simulated with the COMPETES tool. The simulated profits for the year 2030 are used as typical profits for the whole lifetime of the PI-generators.

The Monte-Carlo tool calculates the PI for each PI-generator (see Eq. (1)), which allows for easier comparison than the NPV. A PI of 1 equals breakeven, so profitability indices need to be larger than 1 for a viable business case.

2.4. Research steps

The detailed setup of this study is shown in Fig. 1, where the input data, as well as the capacity optimization, hourly simulation and Monte-Carlo phases are defined.

The input data are discussed further in the Data Section (blocks 2–5 and 10) and Appendix A. Please note that a distinction is made between long-term “scenario” uncertainties (in climate policy and wind penetration), and short-term “case” uncertainties that change between years (in NG:coal price ratio and the wind availability). The scenarios are discrete options that influence the optimal capacity. The cases are based on a continuous dataset, on which quota sampling⁶ is used. Moreover, they affect individual years.

⁵ The computation time of the current study setup was 4 weeks on a 8-core Intel Xeon E5-2650 CPU. Adding more variable input parameters (scenarios or cases) to the COMPETES tool will exponentially increase the computation time.

⁶ Quota sampling is a non-probability sampling approach in which the assembled sample has the same properties as the entire population. In this study, each quantile of the fuel price ratios and wind years is represented by its average value.

Two optimizations of capacity additions to the European power system are performed. In 2020 an optimization is performed to determine which capacity is built in addition to the five exogenously added PI-generators (block 6). This capacity is needed to compensate for retirements in capacity, and increased demand for electricity. Average scenario developments (i.e. C3,P3) and average cases (i.e. G3, Y3) are assumed, resulting in a single optimal mix.

In block 7, new capacity additions for the period 2021–2030 are optimized by optimizing capacity for the year 2030. Runs are performed for each of the five climate policy and five wind penetration scenarios, resulting in 25 (5^2) potential capacity mixes for the year 2030. The G3 and Y3 cases are again fixed. By separately optimizing 2020 and 2030, we account for the uncertainty in future developments when making an investment decision.

Next, hourly MIP simulations are performed for European power system for the year 2030 with COMPETES (block 8). Every combination of the 4 scenarios and cases is individually simulated, based on the optimized generator mixes of block 7. Overall, 625 (5^4) hourly simulations are performed.

In block 9, the discrete COMPETES outputs are fitted on a multivariable 2nd degree polynomial regression to account for the continuous distribution of the wind year cases and the NG:coal price ratio cases. For every PI-generator, both the short-term profits and capacity factors are fitted for 25 regressions: one for each climate/wind penetration combination. Short-term profits are calculated based on the present-day energy only market design. The regressions, as shown in Eqs. (2) and (3), show good fits of $r^2 > 90\%$, as shown in Appendix B. The regressions are used in the Monte-Carlo tool to determine the profits and capacity factor for stochastic price ratios and wind years.

$$\text{Profit}_{\text{PI-generator}(C,P)} = a_0 + a_1 Y + a_2 G + a_3 G^2 \quad (2)$$

$$\text{Capacity factor}_{\text{PI-generator}(C,P)} = a_0 + a_1 Y + a_2 G + a_3 G^2 \quad (3)$$

$$\text{Profit}_{\text{PI-generator}} = \text{Short-term profit (€/MW}_{\text{installed}}/\text{yr})$$

$$\text{Capacity factor}_{\text{PI-generator}} = \text{Capacity factor (\%)}$$

$Y = \text{Wind year}$

$$\left(\frac{\text{MWh}_{\text{wind,year } y} / \text{MW}_{\text{wind,installed,year } y}}{\text{MWh}_{\text{wind,multi-year average}} / \text{MW}_{\text{wind,installed,multi-year average}}} \right)$$

$G = \text{NG: coal price ratio (dimensionless)}$

Finally, the Monte-Carlo business tool is used to determine the PI of the PI-generators and the effect of the uncertainty in input parameters on the PI (block 11).

3. Data

The input parameters underlying the four scenarios/cases as well as the Monte-Carlo tool are presented below. All costs are expressed in €₂₀₁₂.

3.1. Fuel prices

Fuel price projections are adopted from the IEA, see Table 3. Its 6DS, 4DS, and 2DS scenarios determine the coal and CO₂ prices for the C1, C3 and C5 cases (OECD/IEA, 2014c). The C2 and C4 cases are interpolated to provide a smoother output profile. The natural gas prices are derived from the coal price with the NG:coal price ratio cases. These are based on historical and projected ratios from 1990–2014 (World Bank, 2015a) and 2015–2025 (World Bank, 2015b). Natural gas prices differ between countries: they range between 55% and 130% of the average prices in the European Union (EU) in 2010–2014. The deviation from the volume-weighted average price in this period is calculated, and also applied to future prices (Eurostat, 2015a, 2015b).

3.2. Wind power penetration level

Wind power penetration scenarios for 2030 are adopted from IEA and EC projections, see Table 4 (EC, 2011b; OECD/IEA, 2014c). The distribution of the wind capacity is based on projections for 2020, where the low, medium and high penetration distributions are used for the P1, P3 and P5 scenarios (EWEA, 2014). The P1 scenario represents a scenario in which no new capacity is added after 2020, while the P5 scenario projects a doubling in capacity between 2020 and 2030. According to IEA simulations, only the P4 and P5 scenarios are likely to meet the EU target of > 27% renewable energy consumption by 2030 (OECD/IEA, 2014c). An overview of the installed capacity per country is shown in Fig. 2.

3.3. Wind power production

The variation in historical wind speeds and the related wind power production has been quantified based on (1) actual wind power production indices (CBS, 2015a; IWR, 2015; Vindstat.dk,

2015); and (2) historical wind speed patterns of the years 2002–2012 created by Vliet (2015). Vliet based his patterns on ERA-interim weather data (Dee et al., 2011), wind turbine power curves as well as GIS land use, elevation and population density maps (Vliet, 2015).

Wind power production indices and studies on wind power variability show that the standard deviations of annual wind power production ranges from 6–11% of average annual power production (Table 5). This standard deviation is consistent between countries, so a typical standard deviation of 8% is used in this study. No inter-annual autocorrelation in wind power production was observed in long-term wind speeds in Northwestern Europe (Thomas et al., 2009) nor the United Kingdom (Watson et al., 2014).

Five wind year cases are defined with deviations of –20%, –10%, 0%, +10% and +20% of mean annual wind power production. The basis for all five cases are the wind profiles of a single representative year, in order to maintain the relation between wind power production and solar PV power production profiles. The year 2004 is used as a representative year, as the wind power production in this year is most average for all modeled countries over the period 2002–2012.

The wind-year deviations are fully applied to the Dutch wind profiles because The Netherlands are the focus of our study. The annual wind power production in other regions is also adjusted based on the correlation in annual power production with The Netherlands, see Fig. 3. For example, the –10% case results in a 7.5% decrease for the UK because the correlation is 75%.

The changes in annual power production are not applied evenly to every hour, because this is not accurate according to our historical wind speed patterns.⁷ These patterns show that the wind power production in some months correlates more strongly with the annual power production than in other months. Fig. 3 shows this; the months are grouped per season for legibility. This figure shows that changes in the annual wind power production are typically caused by changes in wind power production in specific seasons. For example, wind power production in winter- and summertime has been the main determinant of annual wind power production in The Netherlands and Denmark. In general, wind power production in wintertime is an important determinant of the annual power production.

Climate change may slightly affect wind speeds: projections for the Netherlands for the period 2016–2045 shows that the average wind speed may increase by 0.5% compared to the period 1981–2010. This is smaller than the average variation in wind speeds over 30 years, which is 3.6% (KNMI, 2014). Projections for the Netherlands show that the 30-year average daily wind speed can change by –2 to +8 percent compared to today (Minnen and Ligtoet, 2012). For Europe as a whole, wind speeds could increase or decrease slightly, but uncertainty remains high (Pryor and Barthelmie, 2010). Because of the limited effect and the uncertainty in future developments, we do not account for climate change effects.

3.4. Techno-economic parameters of PI-generator

The techno-economic parameters of the five PI-generator are provided in Tables 6 and 7. Data is based reports by the IEA and previous work of the authors.

Table 3

Overview of climate scenarios and NG:coal price ratio cases.

Climate scenarios	C1	C2	C3	C4	C5
CO ₂ price ^a (€/tCO ₂)	16	23	31	55	78
Coal price (€/GJ)	3.5	3.4	3.3	3.1	2.9
Oil price (€/GJ)	17.4	16.4	15.5	14.4	13.3
NG:coal price ratio cases	G1	G2	G3	G4	G5
NG price (€/GJ) : coal price (€/GJ)	1.94	2.34	2.78	3.15	3.84

^a CO₂ can also be stored for power plants equipped with carbon capture. Cost of transport of €3.5/tCO₂ (Morbee et al., 2012), and cost of storage in saline aquifers of €10/tCO₂ (ZEP, 2011) are used.

⁷ Instead, the hourly production in a given month m and country c is adjusted based on the *monthly correlation* with the annual production of the same country, and the correlation between annual power production of the country c and The Netherlands. Wind cases have values of –20%, –10%, 0%, +10% and +20%.

Table 4
Total installed wind capacity per wind penetration scenario in 2030.

Wind penetration scenario	P1 ^a	P2 ^{b,c}	P3 ^b	P4 ^{b,c}	P5 ^d
Onshore in Europe (GW)	180	220	260	300	340
Offshore in Europe (GW)	18	26	34	42	50
Total in Europe (GW)	198	246	294	342	390
Wind penetration in Europe ^e (%)	10	13	16	19	21
Wind penetration in The Netherlands ^e (%)	12	15	18	23	28
Reference	OECD/IEA (2014c)	OECD/IEA (2014c)	OECD/IEA (2014c)	OECD/IEA (2014c)	EC (2011b)

^a The P1 scenario is equal to the 4DS wind power deployment in 2020. Very little new capacity is constructed.

^b The P2–P4 scenario capacities are within $\pm 3\%$ of DS6–DS2 scenarios capacities of the IEA Energy Technology Perspectives 2014, respectively.

^c The distribution between countries is interpolated from the neighboring penetration scenarios.

^d The P5 scenario is based on the Diverse scenario of the EC energy roadmap 2050.

^e The wind penetration is on an energy bases within the electricity sector: (wind power generated/total load).

Fig. 2. Total installed wind capacity per country per wind penetration scenario in 2030.

Fig. 3. Correlation in annual wind power production with the Netherlands, and correlation of one country's seasonal wind power production with its annual production.

3.5. Monte-Carlo input data

An overview of the variable and fixed input parameters for the Monte-Carlo tool is provided in Table 8. The choice of distribution is based on literature, or calculated from historical time series. The mean values of the distributions are equal to those used in the COMPETES tool. The standard deviations of the investment and O&M costs are set to 10% of the mean, following estimates of Roques et al (2006) and the level of uncertainty of cost estimates used to establish contract prices (called “Class 2 estimates”) (Christensen and Dysert, 2005). The standard deviations of construction time and the plant lifetime are based on the variations in estimates reported in literature. No correlation is assumed between the input parameters unless specifically mentioned.

4. Results

The results are discussed per research phase. Phase 1 shows the expansion of generation capacity, Phase 2 the short-run profits and Phase 3 the PIs of the PI-generators.

Table 5
Reported standard deviation in annual wind power production for different countries and time periods.

Region	Years considered	Standard deviation (%)	Reference
Denmark	2002–2014	7	Vindstat.dk (2015)
Denmark	1978–2008	10	Thomas et al. (2009)
Denmark, Sweden, Finland	1987–2002	10	Holtinen (2005)
Germany	2008–2014	8	IWR (2015)
Germany	1990–2008	11	Thomas et al. (2009)
Netherlands	2002–2014	8	CBS (2015a), (2015b)
Netherlands	1988–2008	10	Thomas et al. (2009)
North France	1990–2008	8	Thomas et al. (2009)
United Kingdom	1957–2011	7	Watson et al. (2014)
United Kingdom	1990–2008	9	Thomas et al. (2009)
Individual EU27	2002–2012	6–9	Own analysis

4.1. Phase 1: capacity investments by COMPETES

An overview of capacity expansions for each combination of climate- and wind penetration scenarios for the period 2021–2030 is shown in Fig. 4. The expansions are in line with the expected, least-cost generator types at each CO₂ price level, as depicted in Fig. 5. Note that nuclear and biomass-fired power plants were also included in the optimization step, but that these were never part of the portfolio of least-cost generators.

Between 38 and 132 GW of new capacity is added to the 650 GW of existing dispatchable capacity in Europe (of which 210 GW hydropower) to meet a peak load of 650 GW. In The Netherlands, between 0.2 and 11 GW is added to 15 GW existing capacity to meet a peak load of 22 GW. This range is caused by the wind penetration scenario (if more wind is installed, less fossil capacity is required), and the geographic deployment of new capacity (more NGCC-capacity is built in The Netherlands due to slightly cheaper natural gas prices in this country).

In the C1 scenarios, coal-fired capacity is built the most because (1) CO₂ prices are low, (2) fuel prices are relatively high, which favors technologies with high investment costs both directly (their

Table 6

Economic parameters of the plants under investigation in this study.

Unit type	Unit size (MW)	TCR investment cost 2020 ^a (€2012/kW)	TCR investment cost 2030 (€2012/kW)	Construction time (yr)	Plant lifetime (yr)	Fixed O&M cost (€2012/kW/yr)	Variable O&M cost (€2012/MWh)
Pulverized coal	750	2070	2070	4	40	25	3
Pulverized coal + CCS	630	3387	3255	4	40	33	5
Natural gas combined cycle	580	897	897	3	30	15	1.2
Natural gas combined cycle + CCS	480	1614	1543	3	30	20	1.8
Gas turbine	100	421	421	1	25	9	0.8
	JRC (2014)	Gerdes et al. (2011), OECD/IEA (2014a)	Gerdes et al. (2011), OECD/IEA (2014a)	IEA (2012)	OECD/IEA (2010)	Brouwer et al. (2015)	Brouwer et al. (2015)

^a The Total Overnight Costs (TOC) reported by the IEA are converted to the Total Capital Requirement (TCR) by including the Interest During Construction (IDC). The IDC depends on the interest rate (8%) and distribution of the overnight costs (equally divided over the construction period).

levelized cost of electricity, LCOE, is relatively better), and indirectly (the electricity price will be higher, which allows technologies with high investment costs to recoup their investments better).

The share of coal is gradually replaced by NGCC capacity in other climate scenarios, and finally by NGCC–CCS. A lot of NGCC–CCS is installed, because it is cheaper to build and operate new NGCC–CCS plants than to operate older existing PC plants.

With increasing wind penetration, the capacity factor of thermal generation decreases. Hence, coal is gradually replaced by NGCC capacity, and NGCC with GT capacity. Also, the total installed fossil capacity decreases with increasing wind capacity deployment.

4.2. Phase 2: short-term profits simulated by COMPETES

The simulated short-term profits of the PI-generators show considerable variations, especially resulting from changing climate scenarios and fuel prices (see Fig. 6 and Appendix B). The scenarios and cases have the following effects:

1. Climate scenarios (C) determine the general level of profits of the PI-generators. Increasing carbon prices decrease PC-operation (even though the coal prices decreases), and promote generators with carbon capture.
2. Wind power penetration (P) does not have a very strong impact. The potential to install wind power capacity in the coming 15 years is relatively limited compared to prognosis of the deployment potential until 2050 (EC, 2011b). This study considers a wind power penetration of 10% in P1 to 21% of annual power

production in P5 (increase of 12–28% of annual power production in The Netherlands). At the same time, the power system can adapt to the changing level of wind power by optimizing addition of new capacity, which improves the integration of wind power (Ueckerdt et al., 2013). Overall, a reduction in electricity prices of about 5% is observed between the P1 and P5 scenario (see Table B.1). Also the capacity factors of PI-generators is reduced by 6–13%. Combined, this reduces the average PI of the PI-generators by 8–12%.

3. The NG:coal price ratio cases (G) have a strong impact on the dispatch of coal and natural gas fired generators. High NG prices increase the dispatch of coal-fired capacity, and increase the electricity price, which increases short-term profits.
4. The wind year cases (Y) cause the saw tooth variations in Fig. 6. Low wind years increase profits and high wind years reduce the profits. This effect is stronger at high wind penetrations. The wind years cases have a stronger impact on the profits than the wind penetration scenarios, because the wind years cannot be predicted and therefore lead to a suboptimal amount of capacity being present in the system.

4.3. Phase 3: Monte-Carlo profitability indices

The distribution of PI values per PI-generator are depicted by probability density functions in Figs. 7–9. The area below each function depicts the likelihood of the PIs to take on a given value, considering the uncertainty in input parameters. Overall, the PI-distributions of the PI-generators have two important properties: (1) the PIs are < 100% and (2) show a large spread, as shown in Fig. 7.

Table 7

Flexibility parameters of the plants under investigation in this study.

Unit type	Min load (% of max load)	Startup cost ^a (€/kW)	Ramp rate ^b (% of max ca- pacity /min)	Min up time (h)	Min down time (h)	No load energy use (GJ/h)	Efficiency 2020 (%)	Efficiency 2030 (%)	Availability (%)
Pulverized coal	25	46	1.7	4	4	251	47	49	90
Pulverized coal + CCS	25	46	1.7	4	4	428	38	40	90
Natural gas com- bined cycle	40	39	2.3	1	1	285	61	62	90
Natural gas com- bined cycle + CCS	40	39	2.3	1	1	360	53	55	90
Gas turbine	35	16	5.0	1	1	152	40	41	90
	Brouwer et al. (2015)	Brouwer et al. (2015)	Brouwer et al. (2015)	Hout et al. (2014)	Hout et al. (2014)	Calculated in this study ^c	OECD/IEA (2014a)	OECD/IEA (2014a)	Hout et al. (2014)

^a All starts are assumed to be warm starts in the COMPETES tool.

^b The hourly ramp rate is 1/3 of the ramp rate per minute, based on the triangular ramping rule.

^c The no-load energy use is calculated based on the unit size and the full-load efficiencies of the generators.

Table 8
Input parameters for the Monte-Carlo analysis and their distribution.

Variable parameters	Distribution	Distribution Reference	Mean	Standard deviation (σ)/options	Standard deviation Reference
Investment costs	Lognormal	Rothwell and Ganda (2014), Vithayasrichar-eon and MacGill (2012)	See Table 6	$\sigma = 10\%$ of mean invest-ment cost	Christensen and Dysert (2005), Roques et al. (2006)
Fixed O&M costs	Lognormal	Rothwell and Ganda (2014)	See Table 6	$\sigma = 10\%$ of mean FO&M	Christensen and Dysert (2005), Roques et al. (2006)
Variable O&M costs	Lognormal	Rothwell and Ganda (2014)	See Table 6	$\sigma = 10\%$ of mean VO&M	Christensen and Dysert (2005), Roques et al. (2006)
Construction time	Lognormal	Rothwell and Ganda (2014)	See Table 6	$\sigma = 20\%$ of mean (NG) ^a $\sigma = 15\%$ of mean (coal) ^a	Brouwer et al. (2015)
Plant lifetime	Normal	Roques et al. (2006)	See Table 6	$\sigma = 12\%$ of mean life time ^a	Brouwer et al. (2015)
NG:coal price ratio per year	Lognormal	World Bank (2015a), (2015b)	2.78	$\sigma = 0.73$	World Bank (2015a), (2015b)
Wind availability per year	Normal	Watson et al. (2014)	100%	$\sigma = 8\%$ of multi-year average	Table 5
Climate scenario	Discrete		See Table 3	5 options (C1–C5) ^b	
Wind power penetration scenario	Discrete		See Table 4	5 options (P1–P5) ^b	
Annual short-term profit	Defined as a function of the scenario parameters based on COMPETES results				
Capacity factor	Defined as a function of the scenario parameters based on COMPETES results				
Fixed parameters			Value	Reference	
Construction cost distribution			c	Gerdes et al. (2011)	
Discount rate			8%	OECD/IEA (2010)	
Unit size			See Table 6		
Efficiency			See Table 7		

^a The standard deviations of construction time and plant lifetime were statistically determined based on the variation in estimates by a range of sources used by Brouwer et al. in earlier work (ECF, 2010; EPRI, 2011; Finkenrath, 2011; GCCSI, 2011; IEA ETSAP, 2010; IEA, 2012; NETL, 2012; OECD/IEA, 2012, 2010; Van den Broek et al., 2011).

^b In our simulations, the middle scenarios (#3, i.e. C3/P3) are considered to be twice as likely as the outer (#1, #5) scenarios. Likelihoods of 0.15;0.2;0.3;0.2;0.15 are assumed for the #1;#2;#3;#4;#5 scenarios, respectively.

^c The construction costs are equally distributed over the construction time.

Fig. 4. Thermal power plant capacity expansions per scenario in Europe and The Netherlands (NL) between 2021 and 2030.

Fig. 5. Least-cost thermal power plant capacity expansion options for the year 2030 for C1–C5 climate scenarios.

The first property signifies that business cases are unsound, which is caused by five factors. First of all, the range in climate policies has a strong impact. Each generator has a specific range of CO₂ prices in which it is the least-cost, and therefore relatively profitable, generator type (see Fig. 5). Outside this range, the generator shifts to a later position in the merit order, which negatively affects its capacity factor, short-term profits and hence its business case. This specifically applies to the PC, and NGCC–CCS

plants, because their relatively high and low emissions make them very sensitive to the different climate scenarios. The NGCC and GT plants are less affected by the climate scenarios because their specific emissions are lower. Secondly, the PI-generators are displaced by newer generators that are built in 2030, which reduces their capacity factor. For example, the average capacity factors of NGCC generators built in 2030 and 2020 in the C3-scenarios are 84% and 75%, respectively. Thirdly, gas turbines are unprofitable because they experience “missing money”: they cannot realize a profit to recoup their investment costs, because they are almost always the marginal (price-setting) generator when they run. This is a direct effect of the modeling approach, in which gas turbines were included even though they would not occur as optimal investments in any of the scenarios. Fourthly, non-linear dynamics in power systems and skewed distributions of input parameters are more likely to increase losses than profits. Lastly, the modeling approach could underestimate the revenues, as discussed in Section 5.3.

The second property, the large spread, signifies major uncertainties in all five business cases. This is a problem for investors because investments must be profitable under a sufficiently wide range of future developments. Moreover, the spread is information that would have been lost if deterministic calculations were performed with a single outcome. Thus, the stochastic analysis can underpin business decisions, as well as policy measures to reduce investment risks.

4.3.1. Effect of climate (C) and wind penetration (P) scenarios

Climate scenarios have a moderate to strong impact on the distribution of PIs, as shown in Fig. 8. They especially affect generators with relatively high (PC) or low (PC–CCS, NGCC–CCS) CO₂ emissions. The NGCC and GT power plants are moderately affected: they both perform best in the C3 climate scenario, where their average specific CO₂ emissions give them an edge over the

other generators. In the other scenarios, the NGCC plant can maintain its spot in the merit order and therefore its capacity factor. The GT plant runs very little to start with, and most of its costs are fixed.

Overall, the uncertainty in climate scenarios strongly shapes the PI-distribution shown in Fig. 7. Without any climate certainty, investors will have to account for all potential scenarios when estimating future profits, which will effectively ruin any business case. This is quantified in Table 9, where it is shown that the mean PIs can improve by 6–42 %-points when future climate policies are known. For example, weak climate policy (C1) favors PC power plants (whose mean PI increases to 68%), and strong climate policy (C5) favors NGCC–CCS power plants (their mean PI increases to 78%). Thus, clearly defined future climate policies effectively steers investors to invest in specific generator types.

Moreover, the spread of the PI-distribution –as measured by the standard deviation– decreases when policies are known, especially for the PC and NGCC-CCS generators. This reduction could further encourages investments. Between the climate scenarios the mean PIs vary strongly, but the spread is hardly affected.

Increasing European wind power deployment from 10% to 21% of the total annual power production reduces the profitability of the PI-generators by 2–8 %-points (Fig. 9, Table 9). This reduction is caused by a 6–13% decrease in capacity factors of PI-generators and a reduction in average electricity prices of 5%. The standard deviation decreases by 0–2 %-points compared to a C3 scenario with wind penetration uncertainty.

Although not as influential as climate scenarios, wind power penetration scenarios still affect the business cases. Formulating long-term national plans can reduce these uncertainties. This

becomes increasingly more important in the decades to come, because the impact of wind power on thermal power plants becomes progressively larger with higher wind penetration (Brouwer et al., 2016; Ueckerdt et al., 2013).

The effect of the NG:coal price ratio cases and wind year cases on the PI distributions is depicted in Appendix B.

4.3.2. Comparison between input parameters

The effect of changing individual stochastic input parameters was quantified to compare the effect of climate and wind-related uncertainties to that of other types of uncertainties. Fig. 10 shows how the mean value of the PI distribution increases or decreases when input parameters are individually varied within their 90% confidence interval. For example, the 5th percentile lowest investment costs decrease the mean PI by 30–59%, and the 5th percentile highest costs increase the mean by 25–68% for the PI-generators.

The climate scenarios have a large impact on the mean PI, which is in line with Figs. 7 and 8. Other important factors are the investment cost and the NG:coal price ratio for coal-fired power plants. They are followed by the wind penetration scenarios and construction times, which have a comparable impact. The remaining four input parameters have a small impact on the mean, including the wind year cases that appear to cancel each other out. The effect of input parameters on the mean PI of the GT plant is relatively large because its mean PI is close to 0%. Also, the fixed-cost parameters have a large impact because the GT plant runs relatively little. Apart from the climate scenarios and the NG:coal price ratio cases, the uncertainty in input parameters affect the PC-(CCS) and NGCC-(CCS) to a similar extent.

4.3.3. Revenue gap

The mean and the spread of a PI distribution can be translated to monetary terms as a revenue gap that has to be bridged to make the business case sound. Fig. 11 shows the average revenue gap of each PI-generator⁸, as well as its standard deviation. The extra revenues mirror the distribution of the PIs: the higher the PI, the smaller the extra revenues, and the larger the spread in the distribution of PIs, the bigger the confidence interval. Moreover, the revenue gap is also expressed in €/MWh terms to facilitate comparisons with other sources. As such it shows the gap that has to be bridged by support policies that remunerate per MWh

⁸ This section reports the average additional revenues that are required to break even, because this is a transparent criterion. In practice, investors are risk averse and will therefore require a higher revenues before they invest.

Fig. 8. PI probability density functions for the C1, C3 and C5 climate scenarios. The Y-axis depicts the relative frequency.

generated.

Fig. 11 affirms the conclusion that investments in new thermal capacity are currently unsound: every generator needs additional revenues. Defining clear climate policies significantly affects the average revenue gap, however, and reduces the spread in PI indices. As a result, reducing this policy uncertainty will boost the profitability of specific generators, and decrease the required support payments by 6–66%. The effect of the wind penetration scenarios is much smaller, but still noticeable.

5. Discussion

5.1. Policy implications

It is highly unlikely that energy companies will invest in thermal power plants given their unprofitable and uncertain business cases. If policymakers want to stimulate investments in new thermal generation capacity, their policies must address two problems of the future power plant business cases. They must (1) increase the PI of new power plants; and (2) reduce the uncertainty of PI distributions. These two goals affect each other, potentially leading to synergies: when reducing the uncertainty in PI, this can affect the mean PI (stronger climate policy will improve the PI of power plants with CO₂ capture, for example). On the other hand, new policies to increase the PI of new power plants will add unforeseen uncertainties to existing power plants.

5.1.1. Profitability

In order to increase the profitability, the revenues of thermal power plants must increase significantly. In a market environment,

Table 9

Statistical properties of PI distributions of each PI-generator per scenario.

Scenarios	PC (%)	PC-CCS (%)	NGCC (%)	NGCC-CCS (%)	GT (%)
Mean of PI distribution (%-point)					
Total	44	39	59	36	–12
C1 (16 €/tCO ₂)	68	27	52	9	–12
C3 (31 €/tCO ₂)	54	38	68	29	–6
C5 (78 €/tCO ₂)	3	52	47	78	–20
P1 (10% wind)	56	39	70	28	–5
P5 (21% wind)	49	35	62	26	–9
Standard deviation of PI distribution (%-point)					
Total	26	13	13	26	11
C1 (16 €/tCO ₂)	12	10	10	9	10
C3 (31 €/tCO ₂)	13	11	11	10	10
C5 (78 €/tCO ₂)	9	10	10	11	10
P1 (10% wind)	13	11	11	10	10
P5 (21% wind)	12	10	11	10	10

this increase in profits could be realized by adapting or changing the current market design (BMW_i, 2014; Levin and Botterud, 2015), or by providing direct support (DECC, 2011; Finon, 2010). Such modifications can introduce new uncertainties, however.

5.1.2. Uncertainty

When aiming to reduce uncertainties, policymakers should first evaluate to what extent uncertainties in input parameters are influenced by policies. Three impact categories can be distinguished:

1. Uncertainties that are strongly affected by policies, such as climate scenarios (i.e. CO₂ prices) and the wind penetration

Fig. 9. PI probability density functions for the P1 and P5 wind penetration scenarios. The Y-axis depicts the relative frequency.

Fig. 10. Effect of variations in individual input parameters on the mean of the PI distribution.

scenarios.

- Uncertainties that are affected by policies, as well as other risks (i.e. economic and project specific risks (OECD/IEA, 2014a)). Most uncertainties fall within this group. The effect of policy uncertainty can be split up in two sub-groups:
 - Policy uncertainty that affects the entry of new generation capacity. The investment cost and the construction time of new investments are affected by policies, particularly those related to permitting and licensing as well as policies to stimulate investments in specific (novel) technologies.
 - Policy uncertainty that affects the operation of the electricity system. These policies affect the variable costs (e.g. by influencing fuel prices), the operation of individual generators (e.g. with feed-in tariffs) or the operation of the power system (e.g. by changing the market design).
- Uncertainties that are not affected by policies, such as the wind

availability per year and market uncertainties.

Overall, policymakers are advised to: (1) start by reducing uncertainties that are strongly policy-driven, aiming for synergies that boost the profitability wherever possible; (2) then evaluate how the short-term profits of power plants can be improved. To minimize policy uncertainty for existing plants, policies that improve the entry of new capacity may be preferable over policies that affect the operation of the whole power system. When designing policies, it is important to ensure that new policies are credible and durable to minimize policy-induced uncertainty in investment decisions. Also, it is important to avoid inconsistencies between policies (OECD/IEA, 2014a).

5.2. Limitations of the analysis

Some elements are not included in the current study, which could affect the results.

- Perfect markets are simulated with COMPETES from a system perspective. As a result, a number of market dynamics that can affect the profitability of power plants is not included in this study. In the capacity optimization phase of COMPETES, exactly enough capacity is built to meet demand. The model does not account for investment cycles due to uncoordinated investments, and the resulting surplus or lack of generation capacity (Arango and Larsen, 2011). Also, as a result, and no and the simulation phase (no market power or strategic bidding occurs).
- Uncertainty in the development of electricity demand is not evaluated in this study. Unexpected reductions or increases in electricity demand would affect the business cases negatively or

Fig. 11. Additional average revenues required to reach break-even per generator. Bars express the revenue gap per unit of capacity (€/kW/yr), while the error bars show the 68% confidence interval. The figures below the bars express the average revenue gap as a premium on top of the electricity price (€/MWh). The P3 and C3 scenarios were fixed when calculating the effect of climate and wind scenarios respectively.

positively, respectively.

- Perfect foresight of iRES power production and generator outages is assumed for unit commitment decisions. Other studies show that stochastic forecasts increase the capacity factors of mid-merit and peak-load plants at the expense of base-load capacity, which may increase electricity prices (Bruninx et al., 2013; Lowery, O'Malley, 2012).
- A single investment decision is made to construct generation capacity, which remains available until the end of its lifetime. No intermediate decisions are considered to decommission capacity or to retrofit installed capacity with CO₂ capture units.
- Only the potential developments in a single year (i.e. 2030) are elaborately optimized and simulated with COMPETES due to computational limitations. Modeling every year throughout the power plant lifetime would be more accurate, but prohibitively computationally intensive with the current model setup.
- The business case of individual generators are stochastically analyzed, but investments in new capacity in the rest of the system are based on a deterministic capacity optimization. In reality, these investment decisions would also be based on stochastic distributions of PIs, which can lead to different, sub-optimal capacity mixes, also because investors in the power sector are risk-averse (Fan et al., 2010). An integrated stochastic optimization, simulation and business case analysis tool like this requires a supercomputer to solve, however (Meyers et al., 2011).
- Demand response, increased interconnection capacity and electricity storage are three options that can improve the (economic) efficiency of the power system as a whole (Brouwer et al., 2016). These options are not included in this analysis.

5.3. Effect of the method on the calculated PIs

A fixed discount rate of 8% is used in this study, which is relatively low considering the low PIs. This may overestimate the PIs because a higher discount rate would further reduce the PIs. Conversely, this study features four assumptions which may lead to an underestimation of the calculated PIs. Still, addressing these assumptions will most likely not increase the PIs to > 100%.

- Perfect markets and perfect foresight are simulated. In practice,

the markets will function sub-optimally, leading to higher electricity prices (Fan et al., 2010). Also, risk-averse investments may result in a sub-optimal electricity mix with higher operational costs, which also increases electricity prices.

- The short-term revenues of the PI-generators are based on a single simulated representative year: 2030. The short-run revenues of PI-generators may be higher in the years 2020–2029 than in the year 2030, however. This could underestimate the PI because the revenues in these early years are discounted less strongly than those in later years and therefore affect the business cases more strongly.
- Ancillary services are not simulated. Reserving capacity to supply reserves may increase electricity prices, and the revenues from ancillary markets may increase the profits of thermal power plants. TenneT reports average an average price of 41 €/MWh for providing balancing power in 2014 (Tenne, 2015).
- Portfolios of power plants are not considered. Combining multiple power plants in a portfolio can hedge results and reduce uncertainty (Rohlf and Madlener, 2014).

5.4. Comparison to other studies

The observed unprofitable business cases of PI-generators in energy-only markets are in line with findings of other deterministic studies for the years 2020–2030 in The Netherlands (Stienstra et al., 2010; Wijk et al., 2014). Moreover, studies on year 2050 low-carbon power systems show that only base-load generators may be profitable (Bertsch et al., 2012; Brouwer et al., 2016, 2015). This study provides more insights into the causes of the uncertain business cases in a quantitative way. Specifically, it shows that only NGCC-CCS could break-even, but only so in the C5 low-carbon scenario. PC-CCS plants have high average capacity factors (88%), but suffer from low average electricity prices. It is hard to quantitatively compare our results to those of stochastic business case studies, because the input data are not aligned. Qualitatively, Yang et al. conclude that the effect of varying CO₂ prices is limited, which can be explained by their low mean CO₂ price of 18.5 €/tCO₂ (comparable to the C1 scenario) (Yang et al., 2008). Roques et al. conclude that investments in NGCC plants are least risky, which is also shown by our analysis (Roques, 2007). This finding is only valid in systems where the amount of generation capacity is in

balance with the electricity demand, however. When too much generation capacity is present, the business cases of NGCC plants can be strongly affected (Brouwer et al., 2014). This effect can be exacerbated by low coal and CO₂ prices, as currently seen in Europe (Parkinson, 2015). Coal prices are currently 25% (14–29%) lower than assumed in this study at 2.5 €/GJ (CBS, 2015b), and the natural gas:coal price ratio is currently relatively high at 3.7 (Eurostat, 2015a). Tuohy et al and Meibom et al. conclude that mid-merit generators are most affected by increasing wind power penetration, which is also shown in our results (Meibom et al., 2008; Tuohy et al., 2009).

The extra required revenues that are shown in Fig. 11 correspond approximately to those reported by other sources. The recent capacity auction in the UK resulting in a clearing price of 25.5 €/kW, which was largely set by existing coal-fired capacity, but also by NGCC plants which are currently under construction (DECC, 2015). As expected, the clearing price for these plants with sunk costs is lower than the revenue gaps calculated in this study (80 €/kW/yr for new PC and 44 €/kW/yr for new NGCC capacity for the C1 scenario). Bertsch et al report a 50–300€/MWh revenue gap for GT plants in 2050, where this study reports a 99–230 €/MWh revenue gap (Bertsch et al., 2012).

6. Conclusion and policy implications

The power sector is changing, and the role of thermal power plants along with it. This affects the projected business cases of new power plants, and increases their uncertainty. This study presents a novel soft-linked unit-commitment/Monte-Carlo tool to stochastically quantify future business cases of thermal power plants. The tool quantifies the soundness of new investments in terms of the mean profitability and its variance, based on partially uncertain input parameters. Particular attention is paid to uncertainty in climate policy and wind power.

The profitability of five thermal power plants that will go online in the year 2020 has been projected with the tool. Our analysis shows that necessary investments in new thermal generation capacity will not be made because business cases are unsound: the mean profitability indices (PIs) are –12% to 59%, while they should be > 100% to be profitable. Moreover, the uncertainty is large (standard deviation of 11–26 %-points). Both issues need to be addressed before new investments are likely to be made.

Focusing on the uncertain input parameters shows that some affect the mean and spread of the profitability index more strongly than others. Future climate policy has a very strong impact (suitable climate policy can increase PIs up to –6% to 78% and reduce their uncertainty), as do investment costs. A range of factors affect the mean profitability to a lesser extent (up to ± 5 %-point change in PI). Regarding wind power, its deployment moderately affects the profitability: 21% wind penetration decreases the mean PIs by 2–8 %-points compared to 10% penetration. Variation in annual wind power production barely affects the mean profitability (variation of ± 1 %-points).

In order to stimulate new investments, policymakers should decrease the uncertainty in projected profitability. Removing policy-induced uncertainties, by providing a credible and durable climate policy for example, is especially important. Second, policies to bridge the revenue gap of thermal power plants should be evaluated –weighing their advantages against new uncertainties introduced by them– and implemented. This combined approach will increase the efficacy of these supportive policies, because projects with smaller uncertainty will require a smaller increase in revenues to be attractive. Clear climate policies can reduce the revenue gap of power plants by 6–66%, for example. Moreover, it means that policymakers should explicitly consider the

uncertainty in business cases when designing policies. The novel, stochastic tool presented in this study is a clear example of how uncertainty can be included.

Lastly, this analysis shows that the business cases of thermal power plants without CCS will become less attractive in low-carbon power systems with higher CO₂ prices and higher deployment of wind capacity. Only power plants with carbon capture may benefit from higher CO₂ prices in a power system in which they have comparatively low CO₂ emissions.

Recommendations for future research:

1. Assess the effect of solar PV on the business cases of thermal power plants.
2. Quantify the effect of flexibility technologies such as interconnector and demand response on power plant business cases.
3. Integrate business case analysis in a stochastic power system model to capture feedback effects.
4. Quantify the effect of implementing policies that increase power plant revenues with a UCED/Monte-Carlo business case evaluation tool.

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Appendix A. Description of tools

Description of COMPETES

COMPETES is a power system optimization tool developed and maintained by ECN. It minimizes the total power system costs whilst accounting for expansions in both generation and transmission capacity as well as unit commitment decisions. The tool is based on complementary modeling (where both primal and dual variables can be constrained together), and optimization modeling (where the least-cost solution is calculated) (Gabriel et al., 2013). The formulation of its components are described in three papers: the unit commitment formulation (Hytowitz et al., 2015), the generation expansion (Özdemir et al., 2013a), and the combined generation and transmission expansion (Özdemir et al., 2015b).

The tool is programmed in AIMMS and can optimize three kinds of problems using the Gurobi solver:

1. Least-cost economic dispatch with perfect competition, based on linear programming (LP);
2. Least-cost unit commitment and economic dispatch with perfect competition, based on mixed integer programming (MIP);
3. Least cost capacity expansion and economic dispatch with perfect competition, based on LP.

COMPETES seeks to minimize the total system cost, which comprises fuel, variable O&M, CO₂, load shedding and, when optimizing capacity expansion, the amortized investment costs. The solution must meet five constraints:

1. Power balance constraint: demand must equal supply at each node in each time step.
2. Generation capacity constraints: units cannot generate more power than their maximum capacity and availability.

COMPETES Future
2030 Aggregated
Existing —
New —

Fig. A.1. Simulated country nodes and geographical scope of COMPETES.

Table A.1

Input data for the COMPETES tool.

Category	Dataset	Reference
Electricity demand	Load profiles Total annual load	ENTSO-E (2015) OECD/IEA (2014c)
Fuel and CO ₂ prices	Fuel price CO ₂ price	Scenario input (Table 3) Scenario input (Table 3)
Power plants	Current capacity ^a Lifetime Future capacity Techno-economic parameters Flexibility parameters	ENTSO-E (2014), Platts (2012) OECD/IEA (2010) Optimized (Fig. 1, Step 6,7) Brouwer et al. (2015), OECD/IEA (2014a) Brouwer et al. (2015), Hout et al. (2014)
iRES	Future wind capacity Wind production profile Future solar PV capacity Solar PV production profile	Scenario input (Table 4) Onshore (Vliet, 2015); off-shore (Hulle et al., 2009) OECD/IEA (2014c) SoDa Services (2014)
Interconnection capacity	Net transfer capacities	ENTSO-E (2015b)

Hydro and geothermal capacities are assumed to stay at the 2015 level, which is a plausible assumption according to IEA projections (OECD/IEA, 2014c). Solar PV capacities are expected to continue to grow from 79 GW in 2013 to 150 GW in 2030. Deployment per country is based on the PRIMES reference scenario, the total installed capacity of which matches the IEA 4DS scenario within 10% (ECN, 2013; OECD/IEA, 2014c).

^a Existing and thermal power generation capacity under construction is adopted from Platts and ENTSO-E (ENTSO-E, 2014; Platts, 2012). Old capacity is exogenously retired based on expected lifetimes of 30, 40 and 50 years for natural gas, coal and nuclear capacity. New thermal capacity additions are optimized by the COMPETES tool.

3. Cross-border transmission constraints: power flows between countries cannot exceed their net transfer capacity.
4. Ramping constraints: the change in power output of a unit between two time steps cannot exceed the ramp rate
5. Integer flexibility constraints (for MIP modeling): minimum load and minimum uptime/downtime constraints. Start-up costs are also included.
6. Profitability constraint (for capacity expansion modeling): the business case of new generation capacity must be profitable, as checked with the combined variable and amortized investment cost and the revenues in the year that the power plant is built. When none of the investment options is sound, the model will charge value of lost load (VOLL) prices to electricity consumers.

Fig. A.2. Overview of input and output data of the COMPETES tool.

Table A.2

Installed capacities in 2030 per European country for the P3 wind penetration scenario. Capacity additions shown in Fig. 4 are not yet included.

Country	Nuclear	Lignite	Coal	NGCC	NG-CHP	GT	Geothermal	Hydro ^a	Wind	Solar PV	Waste	Other	Total (GW)
NL	0.5	0	5.3 ^b	6.0 ^c	1.7	0.4 ^d	0	0	9.3	1.0	0.8	0.7	24
AT	0	0	0.1	1.8	0.6	0.9	0	14.2	6.1	1.5	0.8	0.6	27
BE	5.0	0	0	1.0	1.5	2.3	0	1.4	7.8	4.8	0.4	0.7	25
CH	1.2	0	0	0	0.1	0.1	0	15.0	0	1.6	0.4	0	18
CZ	3.9	2.5	0.7	0	0.3	0.7	0	2.2	1.8	2.1	0	0.1	14
DE	12.1	12.9	16.0	1.0	14.3	5.9	0	16.8	90.6	56.0	1.9	2.8	230
DK	0	0	1.3	0	2.4	0.2	0	0	10.8	0.8	0.3	0.2	16
ES	7.1	2.1	1.8	15.7	5.6	7.9	0	20.7	46.9	18.2	0.3	1.8	128
FI	3.0	0	1.0	0	0.5	0.2	0	3.2	0	0	0	0.9	9
FR	53.1	0	0.3	3.7	0.7	1.9	0	25.2	35.5	14.0	0.9	4.8	140
IE	0	0.4	0.3	2.3	0.7	1.5	0	0.5	7.2	0.8	0	0.9	15
IT	0	0	7.2	3.5	18.0	32.4	0.7	22.0	21.6	28.2	0.8	6.2	141
NL	0	0	0	0	0	0	0	0	9.3	0	0	0	9
NO	0	0	0	0.4	0.1	0.8	0	31.9	0	0.2	0	0	33
PL	0	2.1	3.9	0.2	0.6	1.2	0	2.4	0	0.5	0	0.1	11
PT	0	0	0.6	2.8	0.3	0.4	0	7.3	10.3	11.0	0.1	0.4	33
SE	5.8	0	0	0	0.5	0.4	0	16.6	0	0.2	0.8	1.6	26
SK	2.8	0.1	0.1	0.4	0.1	0.2	0	2.6	0.5	1.1	0	0.2	8
UK	7.6	0	0.1	7.9	8.4	5.4	0	3.9	34.6	8.9	0.4	0.9	78
BK ^e	5.9	2.6	0.3	1.6	3.0	3.6	0	21.4	9.6	0.5	0.4	0.9	50
BT ^f	0	0	2.1	0.5	1.0	0.6	0	2.5	1.3	1.1	0	0.2	9
Total	108	23	41	49	60	67	1	210	303	153	8	24	1045

^a Includes pumped hydro storage.

^b Includes the 750 MW PC and 630 MW PC-CCS PI-generators.

^c Includes the 580 MW NGCC and 480 MW NGCC-CCS PI-generators.

^d Includes the 100 MW GT PI-generator.

^e BK stands for the Balkan region (see Fig. A.1).

^f BT stands for the Baltic region(see Fig. A.1).

Table B.1

Power system indicators of simulated European power systems in 2030.

Key scenario	Scenario code	CO ₂ emissions (MtCO ₂ /yr)	CO ₂ emission reduction Compared to 1990 ^a (%)	Total system costs (G €/yr)	Average electricity price (€/MWh)
C1 (16€/tCO ₂)	C1,P3,G3,Y3	861	38	310	62.1
C3 (31€/tCO ₂)	C3,P3,G3,Y3	737	47	320	68.3
C5 (78€/tCO ₂)	C5,P3,G3,Y3	350	75	345	79.4
P1 (12% wind)	C3,P1,G3,Y3	791	43	320	69.4
P5 (28% wind)	C3,P5,G3,Y3	666	52	320	66.1

^a The European Commission projected that a 54–68% reduction in power system CO₂ emissions is needed by 2030 to meet the 2 °C climate target (EC, 2011a).

Generators

The model optimizes generation decisions for all types of dispatchable power plants. These include 15 types of fossil-fuel fired power plants (which can operate with CCS or as combined heat and power plant), as well as nuclear, geothermal, waste and biomass fired power plants. Moreover, the model includes generation by iRES (onshore wind, offshore wind and solar PV), the generation profiles of which are exogenously defined. The model can curtail excess iRES power production when necessary. Two types of hydropower are included: run-of-river hydro, which is not dispatchable, and hydro reservoirs. The power generation by hydro reservoirs is exogenously optimized based on the residual load in every node. Lastly, electricity storage and demand response can be modeled with COMPETES, but these technologies are not included in this study.

The level of detail of power plants depends on the node. For The Netherlands, individual power plants are simulated, while for the other nodes the power plants are aggregated based on their generation technology and construction year (in blocks of 10 years before the year 2000, and in blocks of 5 years afterwards).

Geographic and temporal scope

The COMPETES tool can simulate the power systems of the EU-

28 plus Norway, Switzerland and the former Yugoslav states, see Fig. A.1. Each country is represented by a single node, except for Denmark, which has two nodes. The tool assumes an integrated EU market where the trade flows between countries are constrained by net transfer capacities. In this study, the Baltic states and south-eastern states are represented by a single node to improve calculation times (Fig. A.1). The model has a time step of one hour, regardless of the optimization type (LP/MIP/expansion). In this study, the year 2020 and 2030 are comprehensively optimized for all 8760 time steps.

Previous work

The COMPETES tool has been used in recent work by ECN:

1. The Dutch National Energy Outlook (Hekkenberg and Verdonk, 2014).
2. A study on the effect of a German capacity market on neighboring countries (Özdemir et al., 2013a).
3. A study on the effect of creating markets for trading power system flexibility (Hout et al., 2014).
4. A study on the effects of intermittent renewables on the power system (Özdemir et al., 2015a).

The COMPETES tool has been successfully validated against historical operation of northwest European power systems for the

Fig. B.1. Overview of the short-term profits per PI-generator for all 625 COMPETES runs for the year 2030.

Fig. B.2. Goodness of fit of regression curves used to transfer power plant profits from COMPETES to the Monte-Carlo tool.

Scope of the COMPETES tool in this study:

1. In this study it is assumed that all regions have present-day energy-only electricity markets.
2. COMPETES can optimize capacity expansions and simulate auxiliary reserves, but neither are not included in this study.
3. The link between the electricity and heat sectors is simulated for The Netherlands by including both CHP plants and electricity generation by industry and the agricultural sector. The SAVE-PRODUCTION model of ECN simulates decentralized electricity production (ECN, 2013). The transport sector is not included in this study.
4. The heat and transport sectors in all other countries are not included.

COMPETES input and output data

An overview of the input and output parameters of the COMPETES tool is shown in Fig. A.2. A detailed overview of input parameters for COMPETES and their sources is provided in Table A.1.

The installed capacities in every country by the year 2030 before the 2021–2030 optimization step are shown in Table A.2. These capacities are based on the installed capacities in 2015, to which the capacity of the 2020 optimization step is added, and from which retirements are subtracted. Retirements are based on technical lifetimes of power plants. The techno-economic parameters of the thermal power generators is dependent on the year in which the generators first came online. These years are grouped in cohorts of 5 years.

Description of Monte-Carlo tool

The Monte-Carlo tool calculates the distribution of PIs of the PI-generators. Its approach can be described in four steps. In step 1, the short-term annual profits of the PI generators are calculated with the multivariable 2nd degree polynomial regression (Eq. (2)). The short-term profits comprise the factors shown in Eq. (A.1). In step 2, the generation per year is calculated from the polynomial regression that describes the capacity factor (Eq. (3)). In step 3, the NPV is calculated with Eqs. (A.1) and (A.2). In step 4, the NPV is converted to the PI with Eq. (1).

$$\text{Profit}_{\text{short-term},y,g} = \sum_{h=1}^h \text{Generation}_{h,g} * (\text{Price}_{\text{electricity},h,g} - C_{\text{fuel},g} - C_{\text{CO}_2\text{tax},g} - C_{\text{CO}_2\text{storage},g}) - C_{\text{startup},h,g} \quad (\text{A1})$$

year 2012. Information about this validation is available upon request.

Fig. B.3. PI probability density functions for different NG:coal price ratio cases. The Y-axis depicts the relative frequency.

$\text{Profit}_{\text{shortterm}}$ = Short-term profit (€/MW_{installed}/yr)
 Generation = Generation (MWh_e/MW_{installed})
 $\text{Price}_{\text{electricity}}$ = Electricity price (€/MWh_e)
 C_{fuel} = Fuel costs (€/MWh_e)
 $C_{\text{CO}_2\text{tax}}$ = CO₂ tax costs (€/MWh_e)
 $C_{\text{CO}_2\text{storage}}$ = CO₂ transport and storage costs (€/MWh_e)
 C_{startup} = Startup costs (€/MW_{installed})
 The profits per year y are calculated per generator g for year hour of the year h .

$$\text{NPV}_g = \sum_{y=1}^Y \frac{\text{Profit}_{\text{shortterm},y,g} - C_{\text{investment},y,g} - C_{\text{FOM},y,g} - C_{\text{VOM},y,g} * \text{Generation}_{y,g}}{(1+i)^y} \quad (\text{A.2})$$

NPV = net present value
 $\text{Profit}_{\text{shortterm}}$ = Short-term profit (€/MW_{installed}/yr)
 $C_{\text{investment}}$ = Investment costs (€/MW_{installed})
 C_{FOM} = Fixed O&M costs (€/MW_{installed}/yr)
 C_{VOM} = Variable O&M costs (€/MWh_e)
 Generation = Generation (MWh_e/MW_{installed})
 i = Discount rate (%)

The profits per year y are calculated per generator g for the whole lifetime of the power plant.

Appendix B: Additional model results

This appendix shows results that give more insight into the method (Table B.1, Figs. B.1 and B.2) and that show the effect of structurally different fuel price ratios (Fig. B.3) and wind years (Fig. B.4, Table B.2).

Power system indicators of simulated power systems

Power system indicators of five key scenarios are shown in Table B.1. As shown, climate scenarios affect all parameters. Changes to the sequence and marginal prices of the merit order affect the emissions and prices. Higher operational costs increase the total system costs. Wind power decreases emissions, electricity prices and operational costs, but their increased capital costs negate any reduction on the total system costs.

Simulated short-term profits for all scenarios/cases

Figs. B.1 shows simulated profits for all five PI-generators for all 625 possible combinations of scenarios and cases. An interpretation of the trends is given in Section 4.2. Please note that the x-axis legend does not mention all data points. Data points depict the Y, G, P and C variables in ascending order.

Goodness of fit of short-term profit regression

The profits of the PI-generators are described with 2nd degree polynomial regressions in the Monte-Carlo tool. The regressions are a function of the NG: coal price ratio and wind year cases, and show a good fit (Fig. B.2). The fit for all technologies except the GT is very accurate (generally $r^2 > 0.95$). The GT shows a slightly lower r^2 (generally $r^2 > 0.88$), which is caused by the stronger sensitivity of these generators to the NG:coal price ratio. For all PI-generators, the worst fit is observed in scenarios where generator runs little (e.g. PC in the C5 scenario, and NGCC-CCS in the C1 scenario), and in which the generator would be unprofitable to start with.

Fig. B.4. PI probability density functions for different wind year cases. The Y-axis depicts the relative frequency.

Table B.2

Statistical properties of PI distributions of each PI-generator for fuel and wind year cases.

Scenarios	PC (%)	PC-CCS (%)	NGCC (%)	NGCC-CCS (%)	GT (%)
Mean of PI distribution (%-point)					
Total	44	39	59	36	-12
G1	19	15	89	49	-8
G3	54	38	68	29	-6
G5	117	76	79	29	0
W1	64	44	0	39	6
W3	54	38	68	29	-6
W5	45	32	0	18	-17
Standard deviation of PI distribution (%-point)					
Total	26	13	13	26	11
G1	13	10	13	11	10
G3	13	11	11	10	10
G5	15	12	13	10	10
W1	13	11	0	10	10
W3	13	11	11	10	10
W5	13	11	0	10	10

Effect of NG:coal price ratio and wind year cases

The effect of changing the mean value of the NG:coal price ratio (P) and wind year (Y) distributions from the #3 case (which is the default in all other simulations) to #1 and #5 cases is explored in this section. These changes are purely hypothetical, because it seems unlikely that fuel prices or average wind speeds will change so drastically (in fact, the whole energy mix is suboptimal when the mean value is changed, because it is optimized for the values of the #3 cases).

A changing NG:coal price ratio has a strong impact on the profitability of coal-fired power plants (Fig. B.3). A lower ratio (G1) lowers natural gas – and therefore also electricity – prices, which reduces the PI of coal fired generators. The positive effect on the operational cost and capacity factor of natural gas-fired generators outweighs the decreased electricity prices, boosting the profitability index of gas-fired power plants. A high ratio (G5) has the opposite effect. It must be noted that changing fuel prices will also affect investments, which will counteract the effect of changes in fuel prices.

The effect of structurally higher or lower wind speeds is assessed by changing the average wind power production (Y3) by –20%-points (Y1) and +20%-points (Y5). Such large changes are very unlikely to happen in the Netherlands, but these runs show what happens to the power system if generation capacity is not in balance with demand (i.e. when the residual load increases (Y1) or decreases (Y5)) (Fig. B.4).

As can be seen, all generators are affected, but natural gas-fired power plants more strongly than coal-fired power plants. As the latter have an earlier position in the merit order, they are less affected by the merit-order effect.

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