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Fuel Switching and Deep Decarbonization

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Fuel-switching and Deep Decarbonization

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Abstract

Fuel-switching is inevitable to achieve deep decarbonization. Humanity has used approximately two-thirds of the carbon budget compatible with the goal to limit global warming to 2 °C. This has, *inter alia*, contributed to growing opposition against the use of coal, prompting an increasing number of countries to announce coal phase-out mandates in the power sector. Advocates of coal phase-outs highlight the expected climate benefits of fuel-switching from coal to gas. However, a narrow focus on coal and gas ignores advancements in low-carbon technologies. I present a simple model to find the least-cost approach to achieve committed climate targets, through fuel-switching in the power sector. A case-study, drawing on the example of Germany, reveals counter-intuitive results that go against conventional assumptions about the role of coal. The findings suggest that, when accounting for stranded assets, a decarbonization pathway that is based on gradual transition to renewable energy and initially retains coal generating assets turns out to be less expensive than a strict coal phase-out.

Keywords: Fuel-switching, deep decarbonization, stranded assets, coal phase-out

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Contents

1 Introduction

Humanity has used up two thirds of the carbon emission budget compatible with the goal of limiting global warming to 2 °C.[1] Global mean temperature has increased by 0.9 °C, and out of the last twenty years, eighteen were among the warmest since 1880.[2] As emissions continue to rise, limiting global warming below 2 °C is widely considered to require substantial policy intervention. As a result, 195 countries agreed to take respective actions in 2015 in Paris.[3]

To reduce carbon emissions, economic theory suggests use of carbon pricing[4] as the most cost-efficient policy instrument.[5] From a welfare perspective, carbon pricing, in the form of a carbon tax or cap-and-trade mechanism, reduces emissions at the lowest cost.[6] However, in practice, policy makers increasingly resort to phase-out mandates to achieve committed emission reductions.[7] As climate policy research focuses on carbon pricing as the first-best option, research into the effects and design of phase-out mandates has lagged behind.

To decarbonize the power sector, the public debate has increasingly focused on phasing out coal power plants. Promoters of coal phase-outs highlight the expected climate benefits of fuel-switching from coal to gas. For every year of coal displacement, fuel-switching to gas adds 1.4 to 2.4 years until depletion to the carbon budget, as gas combustion emits less than half the CO_2 of coal.[8] Therefore, gas may act as a bridge-fuel until zero-emission technologies are available at scale.[9]

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[1] We have used up 1,890 $GtCO_2$-eq of 2,900 $GtCO_2$-eq that preserve a 66% probability to limit global warming to 2°C above pre-industrial time, which refers to the average temperature between 1850 and 1900, see (IPCC, 2013), p. 27; first mentioned by (Nordhaus, 1977), the 2°C bound is commonly used as the upper limit to avoid the worst consequences of climate change.
[2] See (GISTEMP, 2018; Hansen, Ruedy, Sato, & Lo, 2010).
[3] See COP21 Paris Agreement (UNFCCC, 2015).
[4] Definition: "carbon pricing refers to initiatives that put an explicit price on greenhouse gas emissions, i.e. a price expressed as a value per ton of carbon dioxide equivalent (tCO2e)" (Worldbank, 2017).
[5] See (Stiglitz, Stern, & Duan, 2017).
[6] See (Goulder & Schein, 2013).
[7] The poster example is the bans of inefficient light bulbs in the residential sector, see (Tonzani, 2009). In the transport sector, bans of cars from inner cities are increasingly under discussion, see (Möhner, 2018), and the number of announced coal phase-outs in the power sector is growing: e.g. France (by 2022), Sweden (by 2022), Italy (by 2025), UK (by 2025), Austria (by 2025), Finland (by 2030), Netherlands (by 2030) and Portugal (by 2030), see (Powering Past Coal Alliance, 2018).
[8] See (Wilson & Staffell, 2018).
[9] See (Kerr, 2010; Levi, 2013; X. Zhang, Myhrvold, Hausfather, & Caldeira, 2016).

Research has suggested that phase-outs are politically more feasible than carbon pricing at sufficiently high levels,[10] and highlighted their ability to destroy existing structures while creating space for innovation.[11] Phase-out policies are touted as transparent, simple, and influential in creating anti-fossil norms.[12] An example is the nuclear phase-out in Germany, which has been credited with triggering more R&D spending on renewable resources than the Renewable Energy Act (EEG).[13]

And yet, a view that focuses on coal and gas appears too narrow-minded, as it ignores central factors required for answering the question of which fuel-switching strategy is cost-optimal in order to remain on a politically agreed decarbonization pathway. In particular, zero-carbon resources inevitably become necessary at a certain point to remain on the decarbonization pathway, yet existing infrastructure carries the risk of long-term lock-in of high-carbon technologies.[14] This potential lock-in has its roots in power plants that continue operations as they become stranded.[15]

I present a simple model to find the least-cost resource mix, which is consistent with the committed climate targets. Firstly, I explain the intuition and logic of the model. This includes an explanation of how a capacity planner can determine the resource mix in order to cover load demand at least-cost, how climate targets constrain the task, and how carbon constraints switch the roles of fuel types. Secondly, I mathematically formulate the problem so as to numerically determine the least-cost resource mixes which satisfy distinct targets along the decarbonization pathway. Lastly, I solve the model, drawing on the example of Germany.

The case-study, based on the example of Germany, reveals counter-intuitive results that go against conventional opinions on the role of coal. The findings suggest that, when considering stranded assets, a decarbonization pathway that involves the expansion of renewables and includes a continued, but gradually declining role for coal, turns out to be less expensive than a strict coal phase-out. Committed decarbonization targets can still be achieved by adding only minimal new gas capacity. It is more cost-effective to initially keep existing coal resources in the market, and

[10] See (Bertram, Luderer, et al., 2015).
[11] See (Geels, Sovacool, Schwanen, & Sorrell, 2017).
[12] See (Green, 2018).
[13] See (Rogge & Johnstone, 2017).
[14] See (Bertram, Johnson, et al., 2015; Seto et al., 2016; Unruh, 2000).
[15] This 'asset stranding' would be accompanied by devastating wealth loss, distributional impacts, see (Mercure et al., 2018), and potential destabilized the financial system, see (ESRB, 2016). 'Stranded assets' are defined as "assets that have suffered from unanticipated or premature write-downs, devaluations or conversion to liabilities", see (Caldecott, Tilbury, & Carey, 2014), p. 2.

expand zero-carbon technologies. The costs in a scenario with a politically forced coal phase-out are significantly higher, as additional gas resources have to fill the supply gap.

The paper is organized as follows: Section 2 provides the intuition and logic of the model. Section 3 presents the model. Section 4 quantifies the effects, drawing on the example of Germany. Section 5 concludes.

2 Intuition and logic of the model

Fuel-switching in the power sector is inevitable to achieve deep decarbonization. Section 2 introduces the impact of decarbonization on capacity expansion modelling. In the first sub-section, I explain the objective of capacity expansion modelling. In the second sub-section, I explain the implications of climate targets for capacity expansion modelling. In the last part, I explain the effects of decarbonization on the roles of fuel types.

2.1 Capacity expansion modelling

The classic objective of capacity expansion modelling in the power sector is to minimize the cost of power generation. The costs of power generation consist of investment and generation costs, which vary among resource technologies. Generation costs are variable, and depend on the degree of capacity utilization, which is measured by a capacity factor (CF) between zero and one. One denotes full-load operations over 8,760 hours throughout the year. Investment costs are annualized over the life-time of the resource technology.[16]

Based on the technology-specific cost functions, a central planner seeks to find the least-cost resource mix to meet a given load demand. The load demand to be covered can be displayed as a load duration curve (LDC), that is, the annual demand sorted by size, starting with the hour of highest load. The planner finds the least-cost resource mix by mapping the cheapest resource technology for each CF to the LDC.

To illustrative the solution process, for now, assume there are only two resource technologies available. The first one has high investment and low generation cost, while the second one has low investment and high generation cost. An example of this cost constellation may be coal and gas resources, in regions where variable cost of gas fired power generations is more expensive than of coal fired power generation, due to fuel prices of coal and gas. Consequently, if investment cost of gas resources are below those of coal, gas can provide cheaper electricity at low capacity utilization. Yet, at a certain CF, the lower generation costs of coal may offset the higher investment costs. A respective constellation is charted in Figure 1, and, by mapping the cheapest resource

[16] See (Stoft, 2002).

technology for each CF to the LDC reveals the least-cost resource mix; the least-cost capacity by resource technology can be read off the y-axis of the LDC.[17]

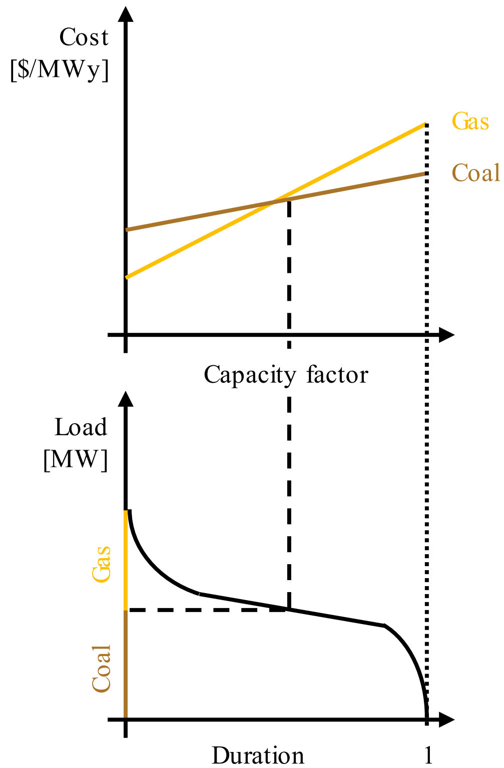

Figure 1: Stylized power system with two technologies.[18]

The illustrated capacity planning model is known as the 'Screening curve method' in energy economics research.[19] The Screening curve method is used to find first-order estimates of the least-cost resource mix to service a given load, as it ignores factors like operational constraints[20] and existing capacity.[21]

2.2 Capacity expansion modelling with carbon constraints

Keeping global warming below 2 °C requires reducing emissions in the power sector. The required emission reductions define an annual carbon budget, which represents the upper limit of

[17] Note: In case of more than two technologies only the intersection points of the cost curves at the upper limit of the trapezoid among x-axis, y-axis and cost curves are relevant.
[18] Own illustration.
[19] The method was originally proposed by (Phillips, Jenkin, Pritchard, & Rybicki, 1969).
[20] See (Batlle & Rodilla, 2013; De Sisternes, 2013).
[21] See (Güner, 2018; T. Zhang & Baldick, 2017).

cumulative emissions over a defined time period. This sub-section explains how a carbon budget constrains the central planner when determining the least-cost resource mix.

Economic theory suggests carbon pricing[22] as the most cost-effective policy instrument to reduce carbon emissions.[23] Putting a price on carbon emissions, for instance through a carbon tax or cap-and-trade mechanism, is found to reduce emissions at a lower cost to society, that is, from an aggregate welfare perspective, than direct regulation such as performance standards or technology mandates.[24] In theory, taxes[25] and tradable permits[26] can achieve equal results, and the preference for one or the other policy instrument ultimately depends on the curving of functions of marginal damage and benefit of emissions around the optimal quantity level.[27]

In the optimization model, a shrinking carbon budget becomes binding at one point in time, and restricts the potential combinations of resource technologies. When solving the model, a binding constraint correlates with a positive shadow price, that is, the marginal cost per unit of carbon in the optimal solution. This shadow price has the exact same effect as a carbon tax at a price level to meet exactly the carbon budget constraint. Consequently, the carbon constraint alters the cost of power generation, in line with the carbon intensity of each resource technology.[28] As a result, low-carbon technologies become increasingly competitive.

2.3 Fuel-switching under carbon constraints

The challenge to limit global warming appears to be more than a capacity expansion problem. The challenge also includes capacity dispatch and replacement, as limiting global warming blow 2°C requires achieving carbon neutrality during the second half of the century.[29] Thereby, a rising carbon price can switch the cost-sequence among resource technologies with dissimilar carbon intensity. This fuel-switching can refer to a complete switch of the cost sequence (i.e. across the entire LDC), or a partial switch for certain CFs.

[22] Definition: "carbon pricing refers to initiatives that put an explicit price on greenhouse gas emissions, i.e. a price expressed as a value per ton of carbon dioxide equivalent (tCO2e)" (Worldbank, 2017).
[23] See (Stiglitz et al., 2017).
[24] See (Goulder & Schein, 2013).
[25] See (Pigou, 1920).
[26] See (Coase, 1960).
[27] Based on (Weitzman, 1974), a large body of literature discusses criteria to rank taxes over cap and trade, see e.g. (Karp & Traeger, 2018).
[28] An analysis of regional differences (USA, China, and Germany) can be found in Appendix 1.
[29] See (UNFCCC, 2015).

Firstly, assume a green field decision, as is the case in a capacity expansion problem. In this case, which involves a long-term perspective, investment cost matters. The introduction of a price on carbon alters the variable cost of generation, and a rising carbon price will make low-carbon technologies increasingly competitive. For instance, coal power plants require an increasing number of full-load hours to offset the lower fixed cost of gas resources. At a certain carbon price, gas resources become cheaper than coal at any capacity utilization. The upper left chart of Figure 2 depicts the constellation when gas resources become cheaper at any CF.

Secondly, assume a brown field decision with existing capacity, as is the case in a short-run dispatch decision. In this case, only marginal cost of power generation matters. The sorted marginal cost of resource technologies – called merit order – determines which resources are utilized to cover load demand. The upper right chart of Figure 2 depicts the constellation where coal and gas resources break even for any capacity utilization. In this case, the fuel-switching potential is limited by the idle capacity of low carbon resources and the current amount of power generated by high carbon resources.[30]

Thirdly, assume a combination of the two previous cases, as is the case in a capacity replacement decision. As existing units fully depreciate prior to leaving the market, investment cost only matter for candidate units.[31] Still, new gas resources become competitive to existing coal resources at a certain carbon price, once the lower carbon intensity of gas (and the relative advantage under a carbon price) offsets higher investment costs. The lower left chart of Figure 2 depicts a constellation where new gas resources break even with existing coal at full capacity utilization. With a further rise in the carbon price, it becomes increasingly attractive to replace existing high-carbon coal resources with low-carbon gas resources. The lower right chart of Figure 2 depicts an intersection point at 10% capacity utilization.

[30] In many countries, the current power generation from coal surpasses the idle gas capacity. The idle gas capacity can therefore be seen as an upper limit of coal-to-gas switching in the short run, as it assumes ideal storage and transmission capacity. See Appendix 2 for an estimate of regional differences (USA, China, and Germany).
[31] As fixed O&M cost are minor (~1% of capital cost), I assume zero fixed cost for existing resources that are fully written-off, see (Güner, 2018; T. Zhang & Baldick, 2017); The term “candidate units” refers to potential new plants.

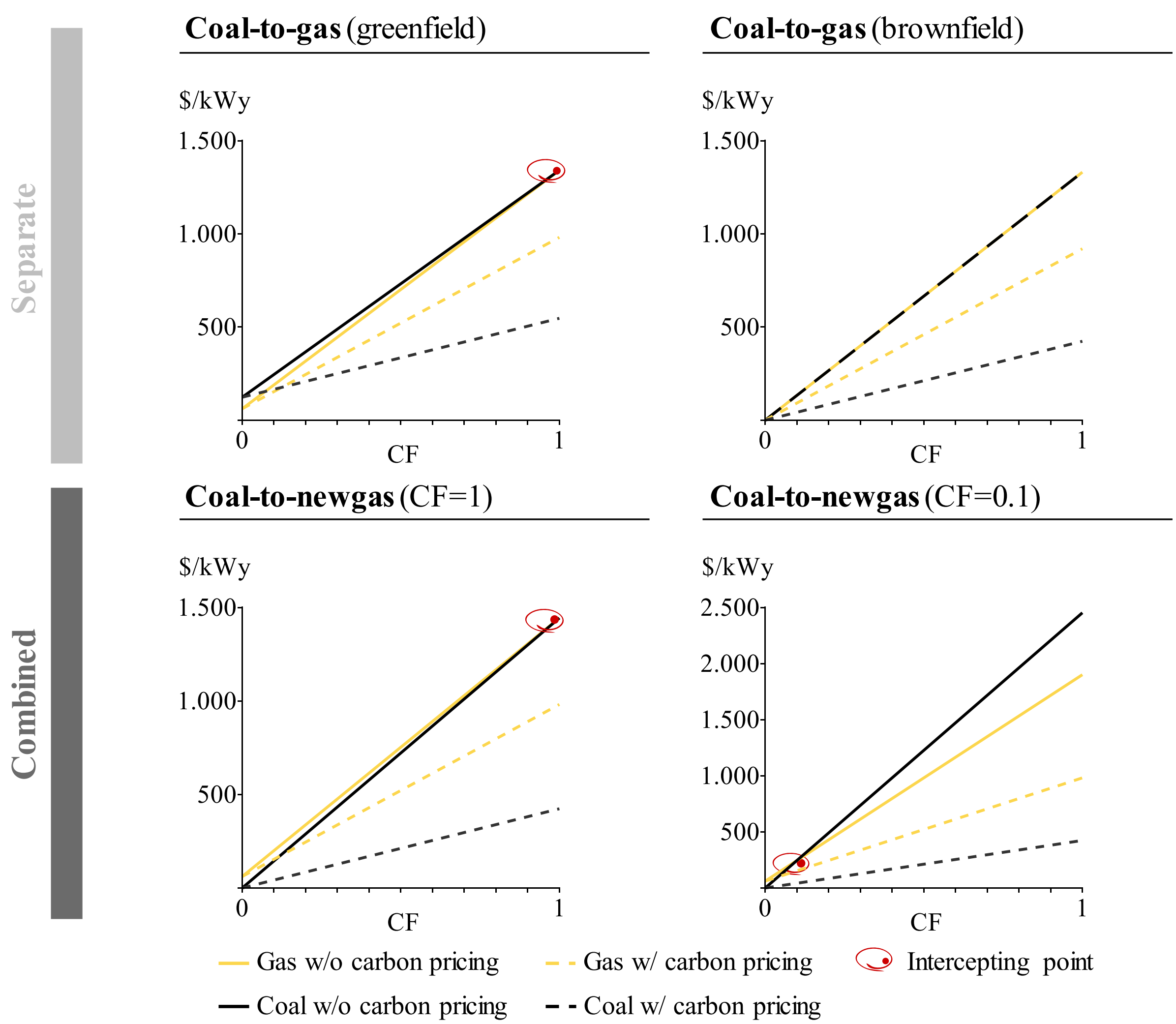

Figure 2: Coal-to-gas fuel-switching under carbon constraints.[32]

[32] Own illustration; The cost functions and carbon intensities are based on German parameters in order to illustrate the relative scale; data sources: carbon emission factors from (UBA, 2017b); cost data from (IEA & NEA, 2015); calculation of annualized fixed cost based on overnight cost assuming 7% interest rate and a plant life-time of 30 years for gas and 40 years for coal-fired power plants in line with (IEA & NEA, 2015); equal split of natural gas in CCGT (Combined Cycle Gas Turbines) and OCGT (Open Cycle Gas Turbines) for Germany as argued in (Schill, Pahle, & Gambardella, 2017).

3 Model: Least-cost power generation with carbon constraints

Section 3 provides the mathematical formulation of the model explained in Section 2.[33] The aim is to quantify cost, timing, and scope of fuel-switching under carbon constraints. As explained in Section 2, the objective is to minimize the average cost of electricity, which is equal to minimizing total system cost (*TC*) for a given load demand. Thereby, *TC* consists of annualized investment cost (*FC*) and variable generation cost (*VC*). In mathematical formulation, the objective function can be expressed as:

$$min\ TC = \sum_{i=1}^{n} FC_i * k_i + \sum_{i=1}^{n}\sum_{j=1}^{m} VC_i * e_{ij}, \tag{1}$$

where k_i denotes resource capacity and e_{ij} produced energy by technology i, in hour j in a certain period:

$$i = 1, \ldots, n \tag{2}$$
$$j = 1, \ldots, m. \tag{3}$$

To incorporate the effect of existing infrastructure, I assume zero fixed cost for existing resources ($i \in$ old).[34] The cost sequence of resource technologies can be summarized as:

$$VC_i < VC_{i+1} \qquad \forall\, i \tag{4}$$
$$FC_i > FC_{i+1} \qquad \forall\, i \notin \text{old} \tag{5}$$
$$FC_i > 0 \qquad \forall\, i \notin \text{old} \tag{6}$$
$$FC_i = 0 \qquad \forall\, i \in \text{old}. \tag{7}$$

The total energy produced by technology i is determinined by:

$$\sum_j e_{ij} = \int_{D_i}^{D_{i+1}} L^{-1}(z)\, dz \qquad \forall\, i, \tag{8}$$

with $L^{-1}(z)$ being the inverse of the load duration curve, and D_i being the loading point. The loading point of a resource technology is determined by the sum of utilized capacities that come prior in the merit order:

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[33] The mathematical formulation of the static cost optimization, considering existing units, is derived from formulations in previous studies, see (Levin & Zahavi, 1984; Murphy & Weiss, 1990).

[34] Fixed Operation and Maintenance cost are minor (~1% of Capital cost), see (Güner, 2018; T. Zhang & Baldick, 2017).

$$D_1 = 0 \qquad \forall\, i = 1 \tag{9}$$

$$D_i = \sum_{l=1}^{i-1} k_l \qquad \forall\, i = 1, \ldots, n+1 \tag{10}$$

$$D_{n+1} = L^m, \tag{11}$$

where L^m represents peak load during the period.

The first constraint of the model is a full coverage of price-inelastic demand at all times, which implies a respective capacity:

$$\sum_i k_i \geq L^m. \tag{12}$$

To illustrate graphically how the first constraint limits the solution space, I again draw on the example of coal and gas resources. As illustrated in Figure 3, all combinations of coal and gas generation equal or greater than demand fulfill the constraint. As the objective is to minimize cost, the optimal combination can be found on the demand constraint line.

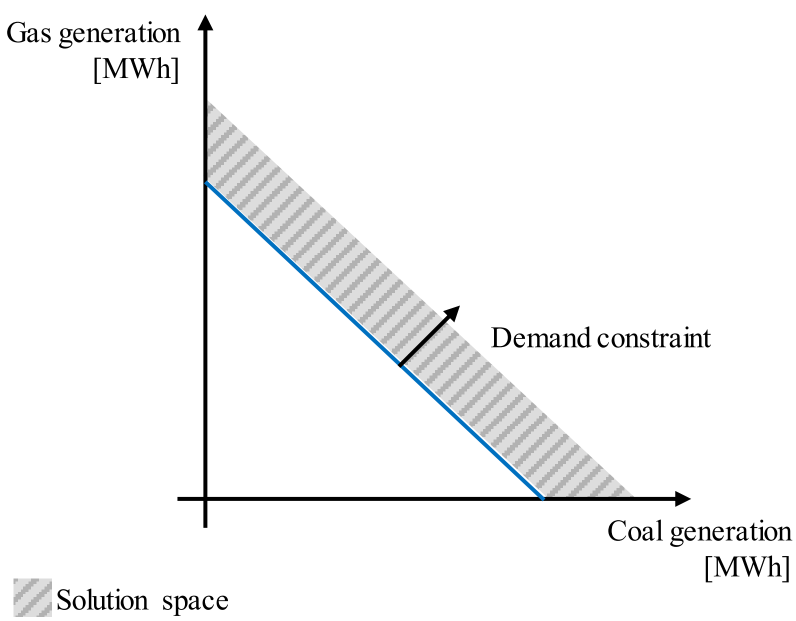


Figure 3: Impact of the demand constraint on the solution space.[35]

The second constraint reflects an annual carbon emissions budget (B):

$$\sum_i \sum_j e_{ij} * C_i \leq B, \tag{13}$$

[35] Own illustration.

where the total emissions are the product of generated energy e_{ij} multiplied by the technology specific emission factor C_i.

Figure 4 illustrates the effect of a binding carbon constraint in two distinct cases: firstly, a carbon budget below the current emissions level, but achievable with a combination of coal and gas resources (Case I). Second, a carbon budget below the current emissions level that cannot be satisfied with any gas-coal-mix (Case II).

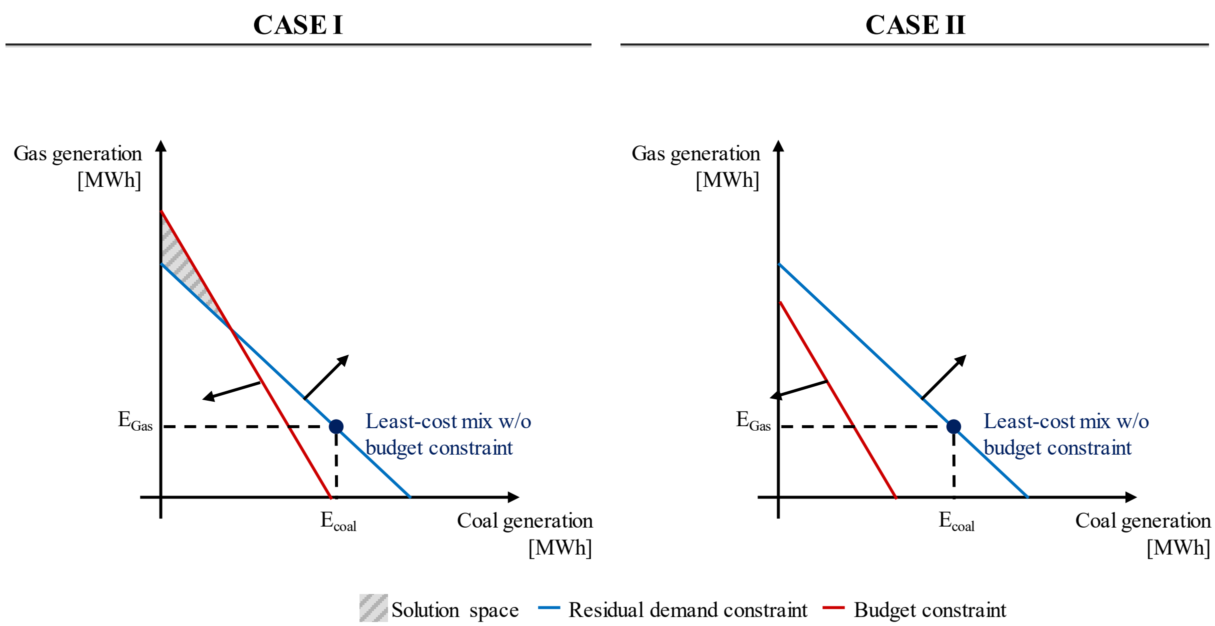


Figure 4: Impact of a tightening budget constraint on the solution space.[36]

To obtain a permissible solution in Case II, a less carbon-intense technology is required. Hence, I introduce 'clean power' as a carbon-neutral technology. Examples for carbon neutral[37] resources are nuclear, renewables like wind and solar, and fossils plus carbon capture and storage (CCS). By deploying such clean power resources, the residual load to be covered by coal and gas diminishes, as illustrated in Figure 5 by shifting the demand constraint down.

[36] Own illustration; note: The slope of the carbon budget constraint illustrates the carbon intensity of both fuel types.
[37] Note: "Carbon neutral" refers to the emissions from power generation. This does not include life cycle emissions, which would include for instance emissions during construction or along the fuel supply chain.

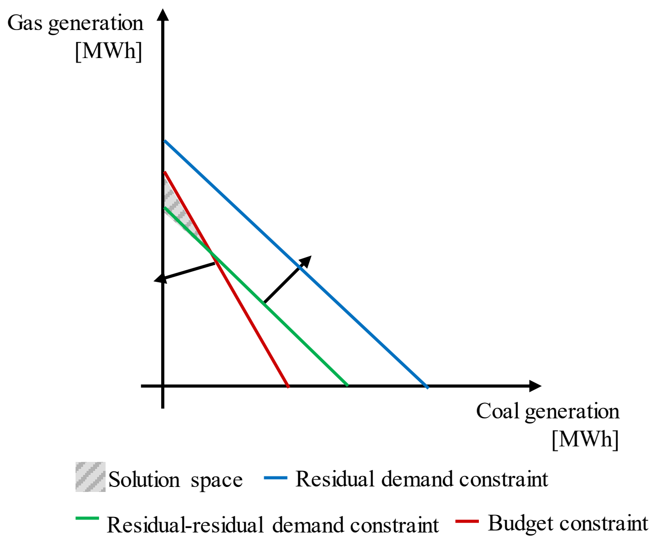


Figure 5: Impact of clean power deployment on the demand constraint and solution space.[38]

The third constraint captures that the installed capacity limits the maximum hourly load:

$$e_{ij} \leq k_i * 1\ \text{h}, \qquad \forall\ \text{i, j,} \qquad (14)$$

and a non-negativity constraint complements the model:

$$e_{ij} \geq 0 \qquad \forall\ \text{i, j.} \qquad (15)$$

[38] Own illustration.

4 Case-study: Fuel-switching and Deep Decarbonization in Germany

To solve the model introduced in Section 3, I draw on the example of Germany. Germany is an example for comparatively ambitious climate targets, as it is committed to a 40% reduction of GHG emissions by 2020, 55 % by 2030, 70 % by 2040, and 80-95 % by 2050, all compared to 1990 levels. Figure 6 charts this decarbonization pathway.

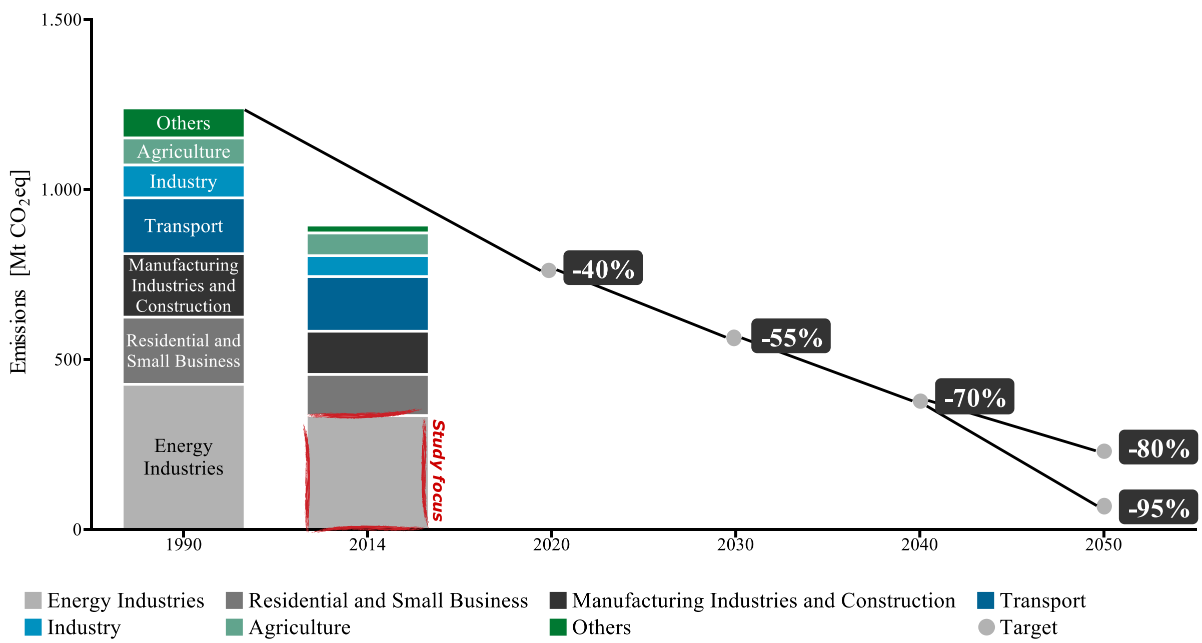


Figure 6: Emissions by sector and German decarbonization targets.[39]

4.1 Model calibration

This sub-section describes the data used to calibrate the model. This includes cost, load, and carbon emission data.

Table 1 depicts annualized fixed and variable costs of lignite, hard coal and gas, based on official statistical data obtained from (IEA & NEA, 2015). Annualized fixed costs are based on overnight cost, which are the sum of all costs to build a respective power plant. These costs can be annualized based on the plant life-time and the respective interest rate. Table 1 further depicts the actual capacity of existing resources.

[39] Own illustration, data source: (BUMB, 2017; UBA, 2017b).

Technology	Overnight cost [USD/kW]	Annualized fixed costs [USD/kWa]	Variable costs [USD/MWh]	Actual capacity [GW]
Lignte	2,054	154	43	21.2
Hard coal	1,643	123	48	25.0
CCGT	974	78	84	14.8
OCGT	548	44	126	14.8

Table 1: Cost data for generation resources in Germany.[40]

To configure the representative zero-carbon technology clean power, three low-carbon technologies appear suitable for deployment at scale: nuclear, renewables plus storage,[41] fossil resources with CCS, or any combination of those.[42] Due to high uncertainty about the future costs and technological feasibility of each resource technology, combined with unpredictability of innovation, I use four cost scenarios: First, I assess the effects of coal-to-gas fuel-switching, assuming no competitive clean power alternative is available. Second, clean power generation is not competitive with existing coal and gas resources in the near-term, but available. Third, clean power generation is close to becoming competitive in the near-term.[43] Finally, I consider a politically forced coal phase-out in 2030.

The cost of clean power in Scenario 2-3 are charted in Figure 7. Figure 7 also charts screening curves of wind and solar to underline the appropriateness of the two levels of cost of clean power. Candidate wind and solar resources are already competitive with existing fossil technologies today. However, their generation patterns follow intermittent natural conditions, and provide power within a limited capacity factor range.[44] Previous modelling work shows a cost-optimal ratio of storage capacity to generation capacity of 2.61 in a system with 100% renewable power supply

[40] Own illustration; data sources: (IEA & NEA, 2015); cost of natural gas as weighted cost of CCGT (Combined Cycle Gas Turbines) and OCGT (Open Cycle Gas Turbines) assuming equal capacity shares in line with (Schill et al., 2017) due to missing data granularity in (UBA, 2017c); calculation of annualized fixed cost based on overnight cost assuming 7% interest rate for fossils and a plant life-time of 30 years for gas and 40 years for coal respectively, in line with (IEA & NEA, 2015).

[41] The increasing number of PPAs for renewables-plus-storage in several U.S. States manifest the assumption to consider these complements as one technology; see (Miller & Carriveau, 2018) for solar-plus-storage PPAs.

[42] See (Jenkins & Thernstrom, 2017).

[43] Note: Lower cost are not considered, as the model targets the residual fossil load share and competitive clean power resources would have been deployed already.

[44] CF of solar PV: minimum 0.13 (residential), maximum 0.34 (utility scale); CF of wind: minimum 0.38 onshore, maximum 0.55 offshore; see (Lazard, 2018a).

from intermitting resources.[45] In 2018, adding the respective cost of storage to the cost functions of wind and solar results in clean dispatchable resources, with costs in between the high and low cost scenarios of clean power.[46]

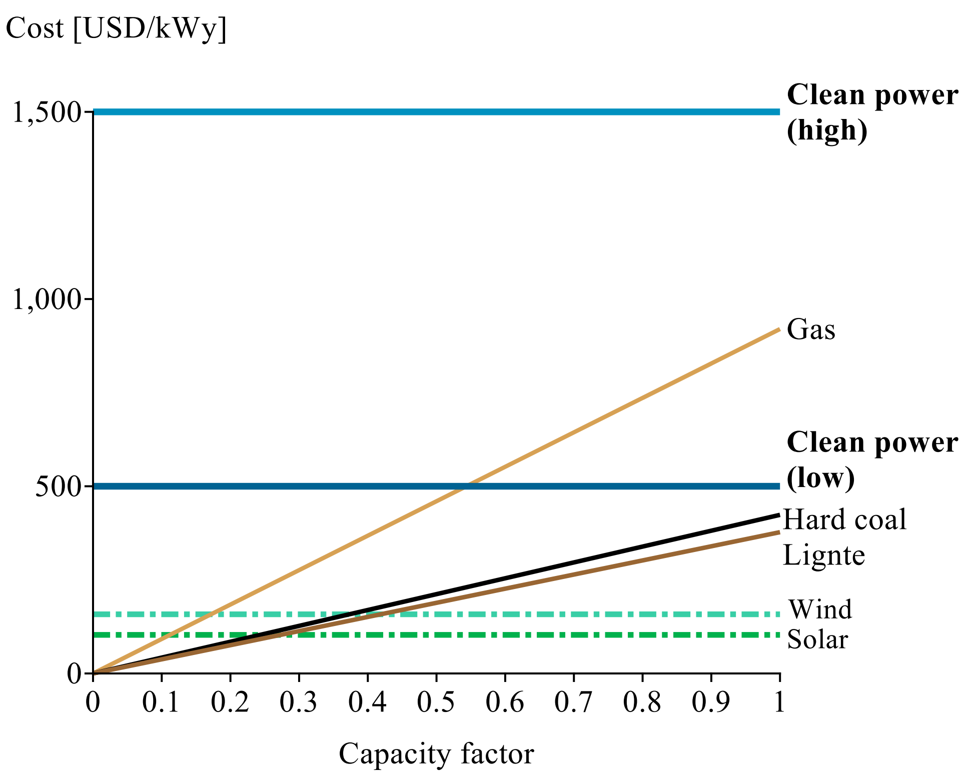


Figure 7: Screening curves of existing fossils and candidate near-zero carbon technologies.[47]

The hourly load data originate from (ENTSO-E, 2017). As scenario forecasts of electricity consumption in 2050 vary in a narrow range, and show no clear direction compared to current consumption, I assume the load duration curve to remain constant.[48] Assuming that existing zero-carbon resources stay in the market, I focus on the residual load demand, which has to be covered by fossil resources, as it is the part that needs to be decarbonized.[49] To determine the residual load,

[45] See (Jacobson, Delucchi, Cameron, & Frew, 2015).
[46] Utility scale lithium batteries start at $251/kWy, see (Lazard, 2018b).
[47] Own illustration; data source: (IEA & NEA, 2015); cost of natural gas as weighted cost of CCGT (Combined Cycle Gas Turbines) and OCGT (Open Cycle Gas Turbines) assuming equal capacity shares in line with (Schill et al., 2017) due to missing data granularity in (UBA, 2017c); calculation of annualized fixed cost based on overnight cost assuming 7% interest rate for fossils and 5% for renewables, as well as a plant life-time of 30 years for gas and 40 years for coal, and 25 years for renewables, in line with (IEA & NEA, 2015).
[48] See (Frauenhofer ISE, 2013; ÖkoInstitut, 2014; Prognos, EWI, & GWS, 2014).
[49] Note: I further assume that existing fossil resources remain available over the period under review, due to parts of the existing fossil generation resources, which have been commissioned recently, German fossil power plant fleet installations by capacity and commissioning year in Appendix 6.

I deduct all non-fossil generation from the load data. This includes the share of net power generation from renewable resources of 38.3 % in 2017.[50] The resulting residual load duration curve is depicted in Figure 8.

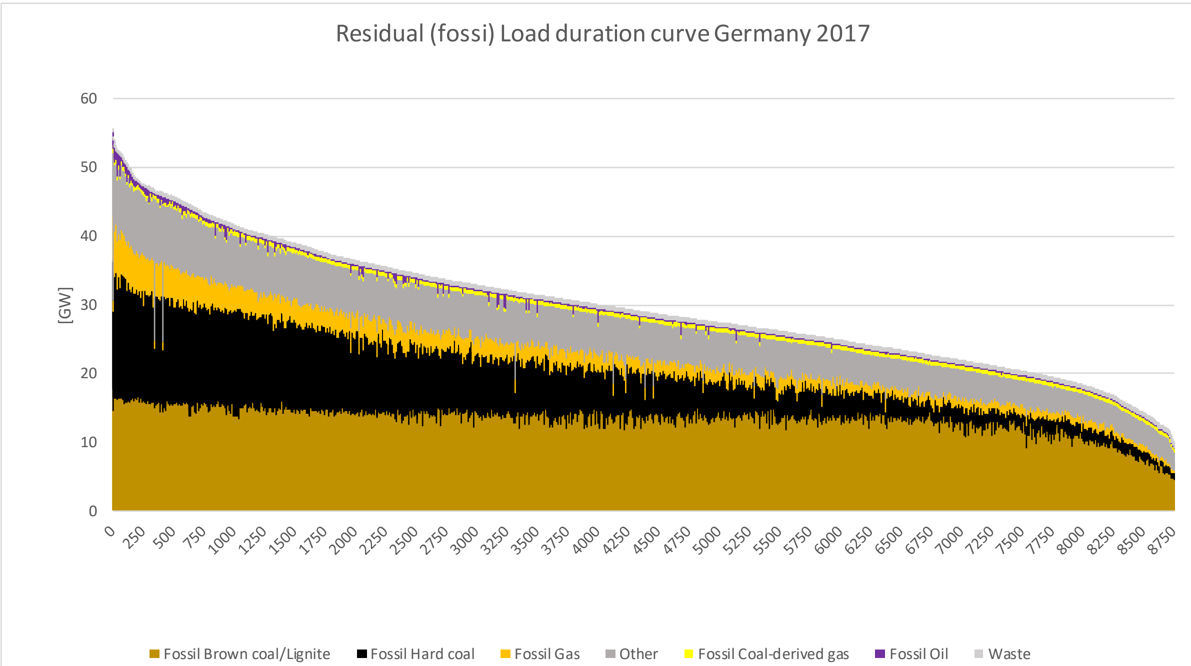


Figure 8: German residual fossil load duration curve.[51]

In the power sector, climate targets require a 61-62% reduction of CO_2 emissions by 2030. By 2050, the German Climate Protection Plan aims for an almost complete decarbonization of the power system.[52] Figure 9 illustrates the specific decarbonization pathway of the power sector.

[50] See (ENTSO-E, 2017).
[51] Own illustration; data source: (ENTSO-E, 2017); the load duration curve can be found in Appendix 3.
[52] See (BUMB, 2017); I use the lower limit of 95% in the case-study.

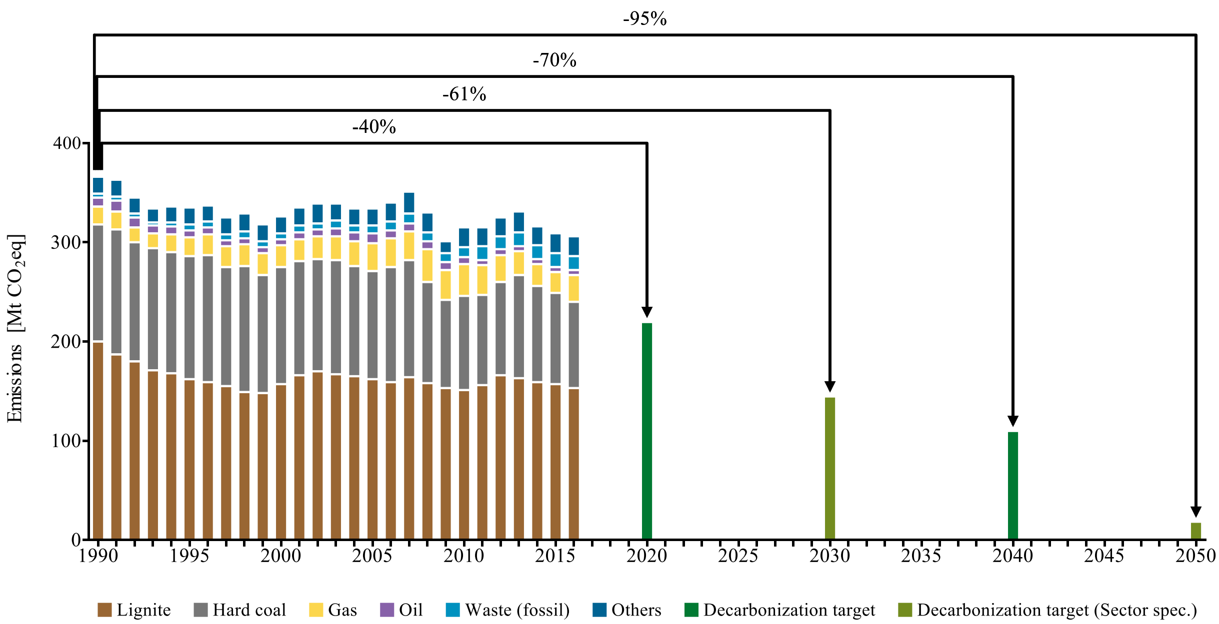


Figure 9: German decarbonization targets in the power sector.[53]

To calculate the carbon emissions of each resource technology, I use the emission factors of lignite, coal, and gas as stated by the German Federal Environmental Agency. The respective carbon emission factors are 1,151 g/kWh for lignite, 863 g/kWh for coal, and 391 g/kWh for gas.[54]

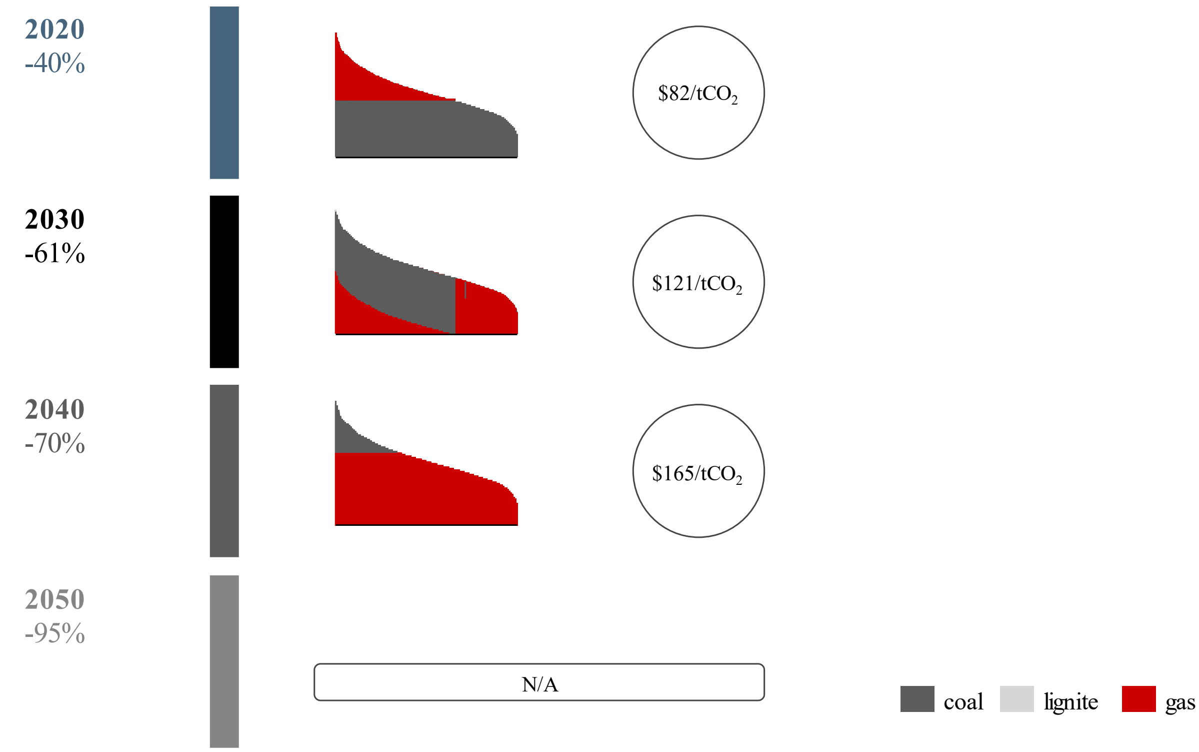
4.2 Model results

Section 4.2 provides the numerical results of the model introduced in Chapter 3, using German parameters as described in the previous section.[55] Section 4.2 is structured along the four scenarios introduced in Section 4.1.

In the scenario without a clean power alternative, to achieve the 2020 target of 40% CO_2 emission reduction, a carbon price of \$82/tCO_2 is needed. Lignite-to-coal fuel-switching occurs at a carbon price of \$18/tCO_2 and \$82/tCO_2 is the break-even point of existing lignite and gas. At \$121/tCO_2 the cost sequence of existing coal and gas switches, which is required to meet the 2030 target. For the 2040 target, additional gas resources have to replace existing coal. At a carbon price of

[53] Own illustration; data sources: (BUMB, 2017; UBA, 2017a); note: The resulting carbon budgets to achieve the targets are 220 Mt CO2 (2020), 143 Mt CO2 (2030), 110 Mt CO2 (2040) and 18 Mt CO2 (2050).
[54] See (UBA, 2017b).
[55] The model is written in GAMS, using a Cplex solver; the model characteristics are summarized in Appendix 4; the source code is depicted in Appendix 5.

$165/t$CO_2$, new gas replaces coal in a CF range of 0.33 to 1.00. However, the 2050 target cannot be achieved with 100% gas power generation. Figure 10 illustrates which resource technology serves residual fossil load between 2020 and 2050 at least cost.



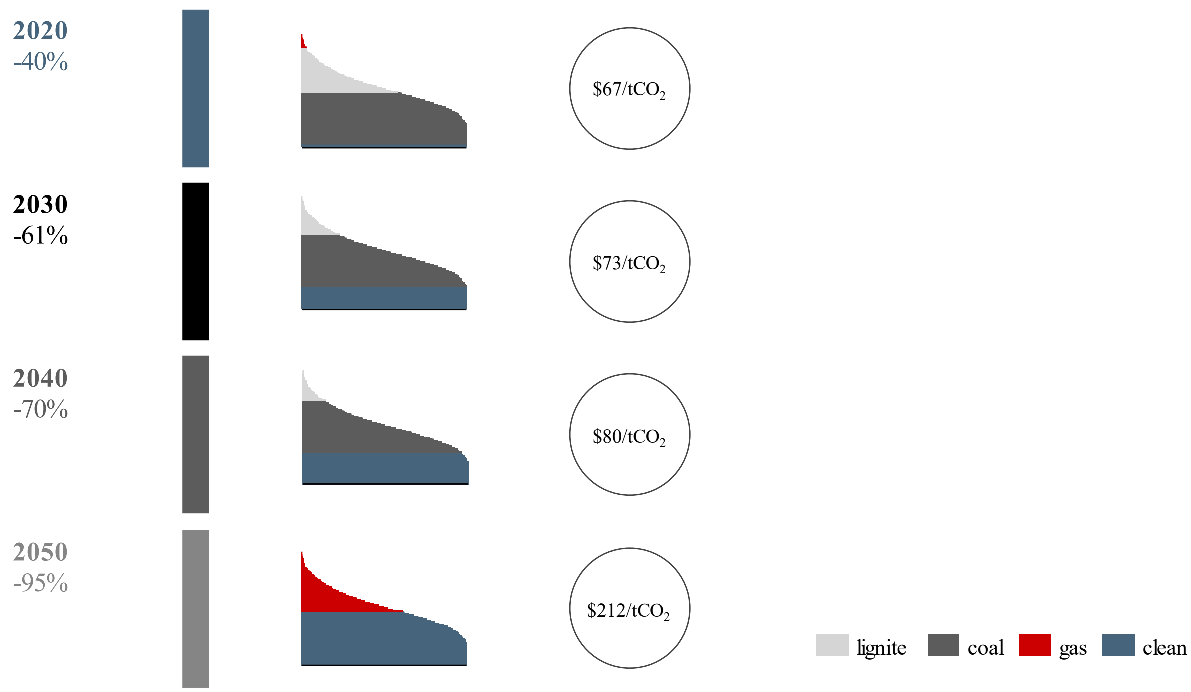
	Capacity [GW]				Generation [TWh]				Cost [USD]	
	Clean	*Gas*	*Coal*	*Lignite*	*Clean*	*Gas*	*Coal*	*Lignite*	*Total [bn]*	*Total [per kWh]*
2020	x	29.2	25.0	21.3	x	21.8	203.8	30.6	13.4	0.05
2030	x	29.5	25.0	0.8	x	166.0	90.2	0.0	21.8	0.08
2040	x	32.5	22.8	-	x	235.8	20.4	-	25.9	0.10
2050	x	N/A								

Figure 10: Least-cost decarbonization pathway (w/o a clean power alternative).[56]

In a scenario with low cost of clean power, a carbon price of $67/t$CO_2$ is needed to achieve the 2020 target of 40% CO_2 emission reduction. Lignite-to-coal fuel-switching occurs again at a carbon price of $18/t$CO_2$, and at $67/t$CO_2$, 1.8 GW of clean power resources become cost-effective. Achieving the 2030 target requires a carbon price of $73/t$CO_2$ to expand clean power to 10.8 GW in order to push the remaining gas and parts of the lignite power generation out of the market. To meet the 2040 target, further lignite capacity has to exit. Expansion of clean power at

[56] Own illustration.

a carbon price of \$212/tCO_2, after a lignite-to-gas switch at \$82/tCO_2 and a coal-to-gas at \$121/tCO_2, ensures achievement of the 2050 target. Figure 11 illustrates which resource technology serves residual fossil load between 2020 and 2050 at least cost. It is noteworthy that no additional gas capacity is required to meet the targets.



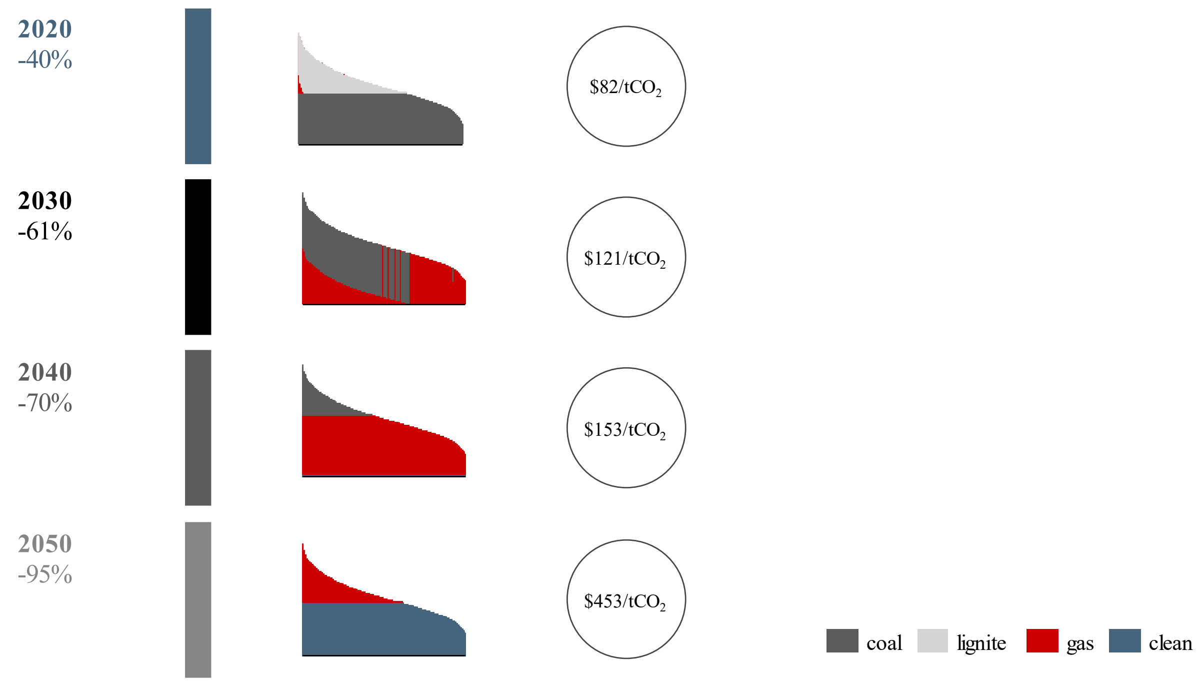
	Capacity [GW]				Generation [TWh]				Cost [USD]	
	Clean (l)	*Gas*	*Coal*	*Lignite*	*Clean (l)*	*Gas*	*Coal*	*Lignite*	*Total*	*Total [per kWh]*
2020	1.8	7.2	25.0	21.3	15.6	0.5	197.8	42.3	13.1	0.05
2030	10.8	-	25.0	19.4	94.8	-	149.2	12.2	18.5	0.07
2040	15.0	-	25.0	15.2	130.8	-	119.8	5.6	21.0	0.08
2050	26.0	29.3	-	-	209.4	46.8	-	-	31.0	0.12

Figure 11: Least-cost decarbonization pathway (low cost of clean power).[57]

In the scenario with high cost of clean power, lignite-to-coal and lignite-to-gas at \$82/tCO_2 are needed. An emissions reduction of 61% occurs at 121/tCO_2 through coal-to-gas fuel-switching, and a carbon price of \$153/tCO_2 triggers an expansion of new gas by 0.3 GW. 95% emission reduction can be achieved at a carbon price of \$453/tCO_2, with gas resources covering CF = [0.04-0.58] and clean power resources covering CF = [0.58-1.00]. Figure 12 illustrates which resource

[57] Own illustration.

technology serves residual fossil load between 2020 and 2050. Again, it is notworthy that only minor additional gas capacity is required to meet the targets.



	Capacity [GW]				Generation [TWh]				Cost [USD]	
	Clean (h)	*Gas*	*Coal*	*Lignite*	*Clean (h)*	*Gas*	*Coal*	*Lignite*	*Total*	*Total [per kWh]*
2020	-	29.2	25.0	21.3	-	21.8	203.8	30.6	13.4	0.05
2030	-	29.5	25.0	0.8	-	166.0	90.2	0.0	21.8	0.08
2040	0.9	29.5	24.9	-	8.2	220.7	27.2	-	25.9	0.10
2050	26.0	29.3	-	-	209.4	46.8	-	-	44.0	0.17

Figure 12: Least-cost decarbonization pathway (high cost of clean power).[58]

In the scenario with a politically forced coal phase-out in 2030, the results for 2020 and 2050 do not change. However, in the interim, additional gas capacity is needed to fill the supply gap. Compared to a phase-out strategy, in a scenario with availability of low cost clean power resources, the phase-out increases annual system cost by $10 billion in 2040; by 2050, the annual additional costs total $7.5 billion. In a scenario with high cost of clean power, the additional costs of a coal phase-out are $6.7 billion (by 2040) and $2.6 billion (by 2050).

[58] Own illustration.

	Capacity [GW]				Generation [TWh]				Cost [USDbn]	
	Clean (l)	*Gas*	*Coal*	*Lignite*	*Clean (h)*	*Gas*	*Coal*	*Lignite*	*Total*	
2020	1.8	7.2	25.0	21.3	15.6	0.5	197.8	42.3	13.1	0.05
2030	-	55.3	x	x	-	256.2	x	x	28.5	0.11
2040	-	55.3	x	x	-	256.2	x	x	28.5	0.11
2050	26.0	29.3	x	x	209.4	46.8	x	x	31.0	0.12

	Capacity [GW]				Generation [TWh]				Cost [USDbn]	
	Clean (h)	*Gas*	*Coal*	*Lignite*	*Clean (h)*	*Gas*	*Coal*	*Lignite*	*Total*	
2020	-	29.2	25.0	21.3	-	21.8	203.8	30.6	13.4	0.05
2030	-	55.3	x	x	-	256.2	x	x	28.5	0.11
2040	-	55.3	x	x	-	256.2	x	x	28.5	0.11
2050	26.0	29.3	x	x	209.4	46.8	x	x	44.0	0.17

Figure 13: Least-cost decarbonization pathway (coal phase-out in 2030).[59]

[59] Own illustration.

5 Conclusions

This paper highlights the need for a broader focus on available technology options when decarbonizing the power sector, as opposed to narrow reliance on a coal phase-out mandate. The case study of Germany illustrates that gradually declining operation of existing fossil resources can play an important role in achieving deep decarbonization at least-cost because it avoids new investment in lower-carbon, but still emitting, gas generation.

Still, phasing out coal will more than likely trigger the deployment of additional gas resources, as shown in the case study of Germany. In practice, a gas power plant commissioned today would not be in operation prior to 2025, and by 2050, the last emitting resource already has to leave the market if the carbon budget is to be met. Given their useful economic life of 35 years, additional gas resources would therefore inevitably become stranded.

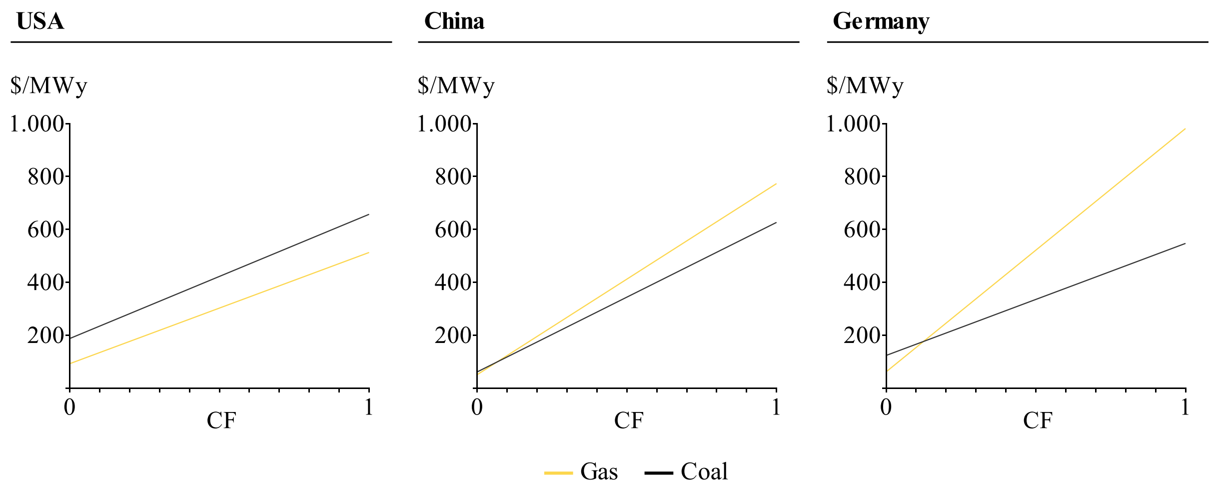
What is more, there is considerable uncertainty about the life-cycle emission factors of gas. Combustion is only the tip of the iceberg, and GHG emissions along the supply chain vary, depending on fuel type, origin, and destination.[60] Novel insights on pipeline leakage[61] and flaring at shale production sites[62] suggest much higher carbon emissions from gas than commonly assumed; climate benefits of gas over coal diminish, or may even reverse in some cases. This aspect has to be clarified prior to assessing the technical feasibility of coal phase-outs,[63] and prior to building new LNG infrastructure.[64]

Not following the coal phase-out trend may generate welfare savings, which could be reallocated, for instance, to subsidize clean power resources. The estimated incremental cost of a strict coal phase-out of up to $10 billion anually is considerable, and rivals the annual financial support for renewable energy sources under German feed-in tariff legislation.[65]

[60] For instance, the carbon intensity of gas depends on extraction (conventional vs fracking), processing (LNG vs w/o liquefaction), storage, transmission (pipeline vs ship vs distance) and distribution; similar of coal (e.g. underground vs surface extraction), and oil as shown by (Masnadi et al., 2018).
[61] E.g. (Alvarez et al., 2018) find for the U.S. that CH_4 leakage along the gas supply chain causes comparable warming as the emissions from combustion.
[62] See (Elvidge et al., 2018).
[63] As put forward by gas lobby sponsored research, see (Agora Energiewende, 2018).
[64] E.g. Subsidized construction of LNG terminals in Europe, see (Bloomberg, 2018).
[65] Note: EEG subsidies, which have triggered a large scale expansion of renewables, totalled €30.4 billion in 2017, see (BMWi, 2018).

6 Appendix

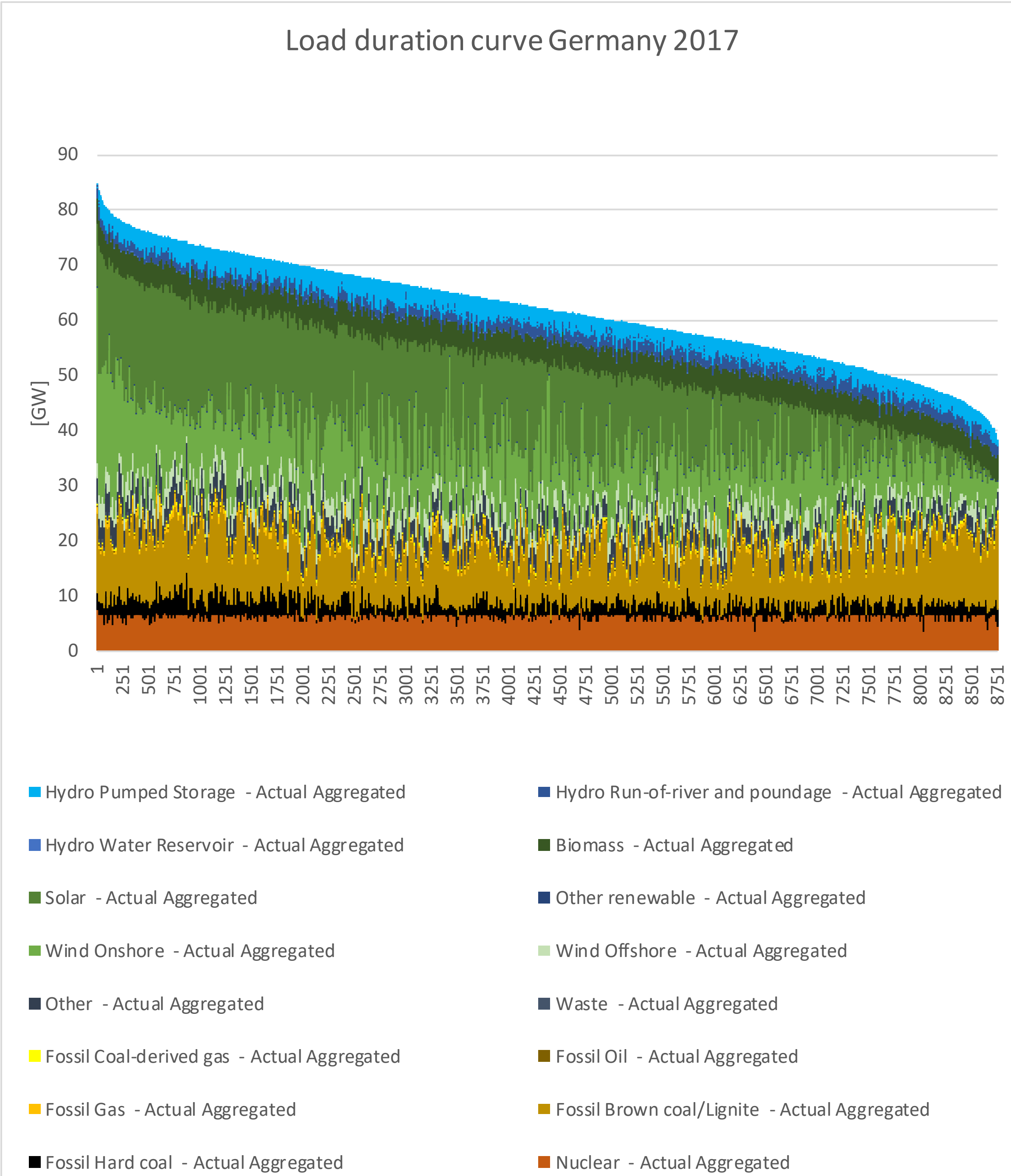
Appendix 1: Regional differences - Screening curves for coal and gas in the USA, China, and Germany. Own illustration; data sources: cost data from (IEA & NEA, 2015); calculation of annualized fixed cost based on overnight cost assuming 7% interest rate and a plant life-time of 30 years for gas and 40 years for coal-fired power plants in line with (IEA & NEA, 2015); equal split of natural gas in CCGT (Combined Cycle Gas Turbines) and OCGT (Open Cycle Gas Turbines) for Germany in line with (Schill et al., 2017); note: Global carbon emission factors lie in a narrow ranges for both coal and gas-fired electricity generation [in gCO2/kWh] (gas in brackets): USA: 0.928 (0.401), China: 0.919 (0.432), and Germany: 0.900 (0.332), see (IEA, 2017).



Appendix 2: Resource capacity and actual generation by fuel type. Assuming a theoretical maximum of 8,760 hours of operation without interruption; data from (Global Energy Observatory, Google, KTH Royal Institute of Technology in Stockholm, Enipedia, & Institute, 2018); note: The idle gas capacity varies from 78 % in China, to 54 % in the USA, and 71 % in Germany, as depict in the right column of the table.

	Capacity [GW]	Generation [TWh]	CF = 1 [TWh]	Current CF
USA				
Coal	327	1,713	2,864	0.60
Gas	291	1,166	2,546	0.46
China				
Coal	829	4,115	7,259	0.57
Gas	60	115	528	0.22
Germany				
Coal	47	285	412	0.69
Gas	24	62	214	0.29

Appendix 3: Actual production by resource type Germany 2017. Data from (ENTSO-E, 2017).



Appendix 4: Model characteristics

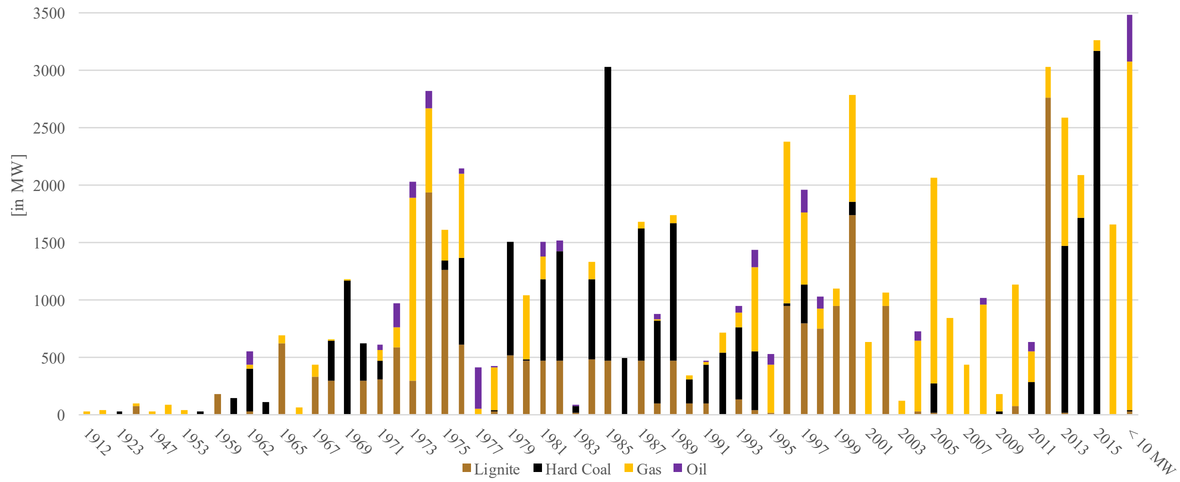
Item	Detailing
Objective function	• Minimize total system costs
Variables	• Capacity investment • Hourly dispatch
Constraints	• Demand coverage • Capacity limit • Carbon budget • Non-negativity
Resolution	• Hourly granularity • Four resource technologies
Input data	• Hourly demand (ENTSO-E, 2017) • Existing capacity (UBA, 2017c) • Technology specific cost (IEA & NEA, 2010, 2015) • Technology specific emissions (UBA, 2017b) • Decarbonization targets (BUMB, 2017)
Assumptions	• Price-inelastic demand • Existing capacity available until 2050 • Resource capacity can be adjusted annually
Equilibrium	• Short-term (hourly/production) • Mid-term (yearly/investment) • Long-term (2020-2050/decarbonization)
Limitations	• No fixed unit expansion size • No economies of scale in supply • No market power of generators • No detailed power plant fleet • No imports/exports • No sector coupling • No transmission cost/constraints • No system service provisions • No cycling cost/ramping constraints • No location-based assessment
Implementation	• Program type: Linear program • Model language: GAMS • Solver: Cplex

Appendix 5: GAMS source code

```
Sets
         i technology /hardcoal, lignite, gas, clean/
         r hour of the year

Parameters
         f(i) fixed cost of technology i [USD per MWy]
         /        hardcoal 123240
                  lignite 154069
                  gas 61362
                  clean 1500000  /
         v(i) variable cost of technology i [USD per MWh]
         /        hardcoal 48
                  lignite 43
                  gas  105
                  clean 0  /
         c(i) existing capacity of technology i [MW]
         /        hardcoal 25048
                  lignite 21288
                  gas  29498
                  clean 0  /
         d(r)   demand (load) in hour r [MW]
         ce(i)  emissions of technology i [t CO2 per MWh]
         /        hardcoal 0.863
                  lignite 1.151
                  gas  0.391
                  clean 0            /
         b carbon emission budget [t CO2]
         /        219600000   / ;

$onecho> tasks1.txt
dset=r rng=a1:a8761    rdim=1
par=d  rng=a1          rdim=1
$offecho
$call GDXXRW resdemand.xlsx trace=3 @tasks1.txt
$GDXIN resdemand.gdx
$Load r
$Load d
$GDXIN

Positive Variables
         k(i)   additional capacity of technology i [MW]
         e(i,r) load of technology i in hour r [MW];

Free variables
         z    total cost;

Equations
         cost         total system cost
         carbon       satisfy carbon budget
         supply(r)    satisfy demand in every hour r
         capa(i,r)    capacity limit of technology i in hour r ;
```

```
        cost..            z =e= sum(i, f(i)*k(i)) + sum((i,r), v(i)*e(i,r));
        carbon..          b =g= sum((i,r), ce(i)*e(i,r));
        supply(r)..       sum(i, e(i,r)) =e= d(r);
        capa(i,r)..       k(i)+c(i) =g= e(i,r);


Model m2 /all/;
Solve m2 using LP minimizing z;

execute_UNLOAD 'capacity.gdx', k;
execute 'GDXXRW.EXE capacity.gdx var=k.l';
execute_UNLOAD 'energy.gdx', e;
execute 'GDXXRW.EXE energy.gdx var=e.l';
```

Appendix 6: German fossil power plant fleet installations by capacity and commissioning year. Data from (UBA, 2017c); note: In case of modification or expansion, the chart shows the date of the latest change as commissioning year.



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