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European electricity sector decarbonization under different levels of foresight

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ABSTRACT

The European Union has set out to reduce the carbon intensity of its electricity generation substantially, as defined in the European Roadmap 2050. This paper analyses the impact of foresight towards decarbonization targets on the investment decisions in the European electricity sector using a specific model developed by the authors called dynELMOD. Incorporating the climate targets makes the investment into any additional fossil capacity uneconomic from 2025 onwards, resulting in a coal and natural gas phase-out in the 2040s. Limited foresight thus results in stranded investments of fossil capacities in the 2020s. Using a CO_2 budgetary approach, on the other hand, leads to an even sharper emission reduction in the early periods before 2030, reducing overall costs. We also find that renewables carry the major burden of decarbonization; nuclear power (3rd or 4th generation) is unable to compete with other fuels and will, therefore, be phased out over time.

1. Introduction

Reducing the carbon emissions from the electricity sector is an essential element of any low-carbon energy transformation strategy, essentially because mitigating emissions in other sectors is more challenging and costly. Europe has set out particularly stringent targets for the low-carbon energy transformation: it has set a binding target of 40% greenhouse gas emission reductions until 2030 (basis: 1990), and a (non-binding) target of 80–95% reduction by 2050. Already the European Union (EU) “Reference Scenario” of 2011 (such long-term energy projections are carried out EU-wide every three years) did foresee an almost complete decarbonization of the electricity sector, with only 2% of the 1990 carbon dioxide (CO_2)-emissions remaining by 2050 [1]. In doing so, it relies on a combination of fossil fuels, some of which is equipped with carbon capture, nuclear, and some renewable energy sources. The paper analyzes different pathways of decarbonizing the electricity sector in Europe at the horizon 2050. In particular, we sketch out scenarios of the transformation of the European electricity sector and discuss the implication of different assumptions on the foresight of the actors, such as perfect foresight, myopic foresight, and a budgetary approach where CO_2-emissions can be allocated freely over the entire period from 2020 to 2050.

To assess the impact of policy instruments and their ability to achieve climate change policy objectives different kinds of models are used: Pfenninger et al. [2] classify models according to different challenges they address. The majority of models – including computable general equilibrium, integrated assessment or energy system models – are able to convey the “big picture” of what is happening, often for a global scale [3–7]. Additional studies focussing on specific regions or continents are able to include further regional characteristics [8–11]. These model outcomes are important to prove that a decarbonization of the entire energy sector is technically possible. The models are often able to cover several sectors, including aspects of the heating and transport sector, linking them e.g. through endogenous fuel substitution. The disadvantage of such comprising models, however, is that their outcomes are too general for a detailed examination of the electricity sector and mostly neglect electricity grid characteristics and

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limitations. The scenarios by the European Commission (EC) [12–17] for forecasting the development in the energy sector are based on the integrated energy system model Price-Induced Market Equilibrium System (PRIMES) [18,19].

Partial equilibrium investment models in turn only focus on some sectors, but are able to implement a much more detailed representation of the analyzed sector. The models differ in their temporal or spatial resolution and electricity grid representation, or implementation of uncertainty or stochasticity, and some include myopic foresight of the investment decision.

In the following we focus on models and literature with an emphasis on aspects of foresight in the electricity sector. Reducing the foresight of the model could furthermore reduce the computation time of models and therefore allow for an increased detail of representation. Babrowski et al. [20] switch from a perfect foresight to a myopic approach to reduce the computation time of their model runs to one tenth. Overall results, however, vary substantially in scenarios that do not assume steady development of parameters. The latter is especially the case in scenarios in line with climate targets which imply stronger changes over time and consequently result in different predictions under various foresight assumptions. Keppo and Strubegger [21] agree with this, observing the biggest differences with respect to stronger reliance on conventional energy sources and less deployment in new technologies resulting in higher costs when modeling a myopic approach. This is being supported by Johnson et al. [22]; highlighting the risk of breaching climate targets at the cost of overall welfare reduction and additional stranded carbon intensive capacities. Using a myopic approach therefore not only decreases the computational time but might also be able to replicate short sighted behavior of (political) actors. Poncelet et al. [23] hereby stress the importance of accounting for trends within the foresight period in a myopic approach, e.g. with respect to profit gains, to allow for a better representation of reality.

Regarding the grid representation, transport models are used in Ludig et al. [24]; Haller et al. [25]; Schmid and Knopf [26]; Hirth [27]; Pleβmann and Blechinger [28]; Möst and Fichtner [29]. A more detailed representation of the characteristics of the underlying transmission infrastructure is often done using power transfer distribution factors (PTDFs) or direct current (DC) load-flow approximations, such as in Richter [30]; Fürsch et al. [31]; Hagspiel et al. [32]; Stigler et al. [33]. Stochasticity and uncertainty are implemented in EWI and Energynautics [34]; Jägemann et al. [35]; Spiecker and Weber [36].

The model applied in this paper called dynELMOD (**dyn**amic **El**ectricity **Mod**el) is a dynamic partial equilibrium model of the European electricity sector which determines cost-effective development pathways for investments into generation and transmission over time. It implements not only a good representation of the underlying grid infrastructure on a country level but also is able to represent different levels of foresight in the investment decision. It first decides the investment in conventional and renewable generation and network capacities for the European electricity system and in a subsequent step calculates the dispatch for an entire year based on the investment results.

This paper is structured in the following way: the next section describes the dynamic investment model of the European electricity market, called dynELMOD, which is a result of a decade of modeling work on electricity markets. Section 2 also describes the main data used in the model, including a survey of cost estimates for low-carbon technologies. Section 3 contains the definition of the scenarios, Section 4 the main results of the model calculations; in addition to the main scenarios we distinguish between a world with perfect foresight, one with myopic foresight, and one with an overall CO_2 budget available to the decision makers. Section 5 provides a discussion of the results including an hourly simulation of the resulting electricity system, and Section 6 concludes.

2. Methods

2.1. dynELMOD: a detailed model of the European electricity sector

We apply the dynELMOD framework from Gerbaulet and Lorenz [37]; which is a dynamic investment and dispatch model for Europe formulated as a linear problem and solved with the General Algebraic Modeling System (GAMS). The objective is to minimize total system costs in Europe until 2050. To do so, the model can decide endogenously upon investments into conventional and renewable power plants, different storages including demand side management (DSM), and the high-voltage electricity transmission grid. This determines the solution space for the resulting power plant dispatch and electricity flows between countries. While for the investment decisions a reduced time frame is considered, the dispatch calculations are done in a subsequent step with a full year and checked for system adequacy. The time frame reduction technique allows to represent the general and seasonal characteristics of an entire year but also to achieve a continuous time series for renewables feed-in and electricity demand including times with low solar radiation and little wind in-feed. dynELMOD determines investments into electricity generation capacities in 5-years steps with a variable foresight length. The underlying electricity grid and cross-border interaction between countries is approximated using a flow-based market coupling approach based on a PTDF matrix. It is derived from a full-fledged node- and line-sharp representation of the European high-voltage electricity system. Relevant boundary conditions are the CO_2-budget, decommissioning of existing plants after the ending of their lifetime and the electricity demand development. The mathematical formulation can be found in Appendix A.

2.2. Data

The data used describes the essential characteristics of the European electricity sector, including demand, electricity transmission, and generation and storage technologies. We use input data and assumptions provided in Gerbaulet and Lorenz [37] that are published under an open source license. This dataset includes 33 countries, each represented with one node and located within five different synchronous areas (Fig. 1). The anticipated development of the existing power plant portfolio serves as the baseline upon which investments into new generation capacity can be built. Potentials and different resource grades for renewable energy sources (RES) are included on a country resolution.

An essential element of any dataset is the assumption about future investment costs. dynELMOD relies on an extensive survey of the literature carried out over the last years and documented in the DIW Berlin Data Documentation 68, published by Schröder et al. [38] and updated over time using newest studies and expert estimates. Fig. 2 summarizes the main assumptions of how investments costs are likely to evolve.

Nuclear power investment costs have gone up systematically over the last decades, as observed by Joskow and Parsons [42]; Grubler [43]; Rangel and Lévêque [44]. Consequently, the EU Reference Scenario 2016 has increased its estimates from 4,500 €/kW to 6,000 €/kW [45].[1] The International Energy Agency (IEA)

[1] “Compared to the previous Reference Scenario costs of nuclear investments have been increased by over a third and the costs for nuclear refurbishments have also been revised upwards” [45].

and the Nuclear Energy Agency (NEA) have also analyzed investment cost of nuclear power plants in a recent study. The findings show investment costs at about 4,500 €/kW [46]; 41) for new-built nuclear plants in Europe.

Cost estimates for renewables rely on many figures provided by industry and independent experts. We expect the cost degression of solar photovoltaic (PV) to continue, though at a slower pace over time; onshore wind also has a positive, but significantly less steep learning curve. The estimates for offshore wind are subject to a much higher uncertainty. Biomass is expected to remain by far the most expensive renewable source.

Cost development estimates for storage and DSM technologies are based on Pape et al. [39]; Zerrahn and Schill [40]. These estimates do not only include a cost component in €/kW which represents the installed power, but also a cost component in €/kWh which describes the installed storage capacity itself. The levelized cost of energy (LCOE) of storage use itself is not an input parameter, as the storage dispatch and the amount of storage usage significantly influences the result. dynELMOD itself determines the installation of power and capacity for the storage technologies separately, as well as the storage usage in a single optimization step. The model can also endogenously influence their proportion (within bounds) if the technology allows. For assumptions about costs for carbon capture, transport and storage (CCTS) technologies, which can be implemented as a sensitivity but are not included in the default model runs, we follow the optimistic forecast by the industry to propose a technology that is not yet available at commercial scale [38,41].

3. Scenarios

We apply dynELMOD to three scenarios representing degrees of planning foresight regarding the decarbonization pathway until 2050. Our objective is to analyze the development of the European electricity sector under different boundary conditions. dynELMOD can present different scenarios of how decision makers deal with information: The knowledge (or lack thereof) how the electricity sector's future boundary conditions will evolve can have a substantial impact on the investment decisions done over time. Therefore, we test different assumptions regarding the planner's foresight:

- The *Default Scenario* anticipates an overall moderate electricity demand increase as well as an almost complete decarbonization of the electricity sector in Europe until 2050. It serves as a reference for the other scenarios. It assumes perfect foresight over the entire horizon (2015–2050). The central decision maker faces a yearly linearly decreasing CO_2 constraint, which reduces carbon dioxide emissions by 2050 to only 2% of the current level, reaching an almost 100% decarbonization of the

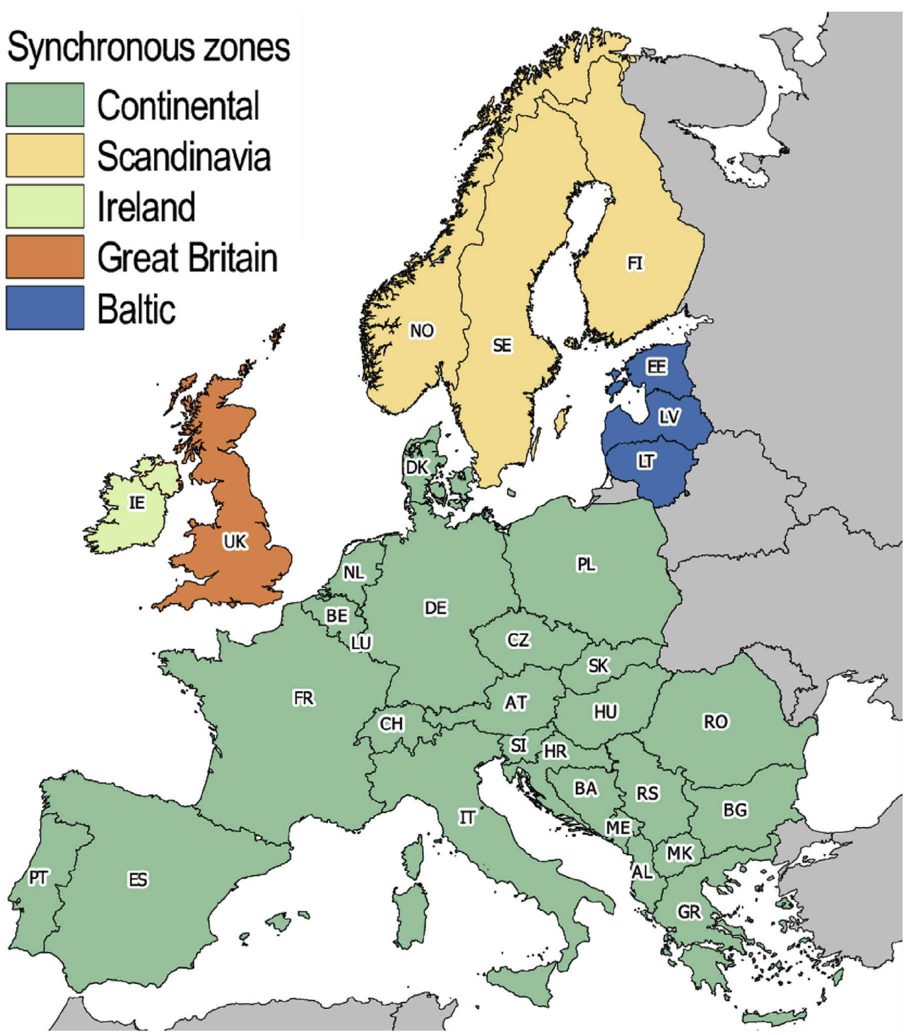

Fig. 1. dynELMOD geographical coverage.

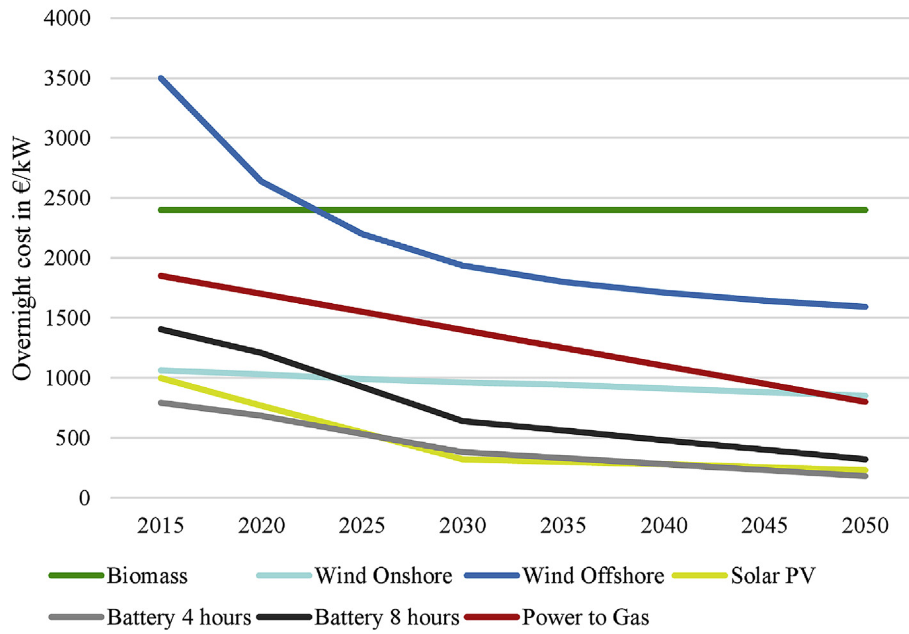

Fig. 2. Investment cost assumptions for selected technologies. Sources: Gerbaulet and Lorenz [37]; Pape et al. [39]; Zerrahn and Schill [40]; Oei and Mendelevitch [41]; Schröder et al. [38].

electricity sector, which is in line with many scientific studies in the literature (compare [47]).

- By contrast, a *Reduced Foresight* scenario considers that the decisions makers are only aware of the CO_2 target of the upcoming five-year period, and thus behave "myopically." The purpose of this scenario is to model possible short-sightedness of politicians due to election cycles as well as investors' limited trust in long-term (environmental and) political targets. The results should therefore identify the danger of stranded investments resulting from such short-term vision.
- An alternative scenario to reflect a different CO_2 allocation mechanism is implemented in the *Budget Approach*: decision makers receive an aggregate emission budget covering the entire period from 2015 up to 2050 ($\approx$22.5 bn. t of CO_2), and then can use this budget at their discretion over the period. An additional constraint is that the annual emissions in 2050 are not allowed to exceed 2% of 2015 CO_2 emission levels. The latter guarantees that CO_2 emission levels beyond 2050 will be close to zero in all scenarios. The budget approach has become popular among climate policymakers and academic researchers recently as climate change is mostly influenced by overall emissions no matter of their date of release. Adjusting the mathematical constraints accordingly allows decision makers a higher degree of decision making resulting in an optimal emission allocation at lower overall costs. In general, abatement decisions are expected to be taken earlier to "save" emission rights for the final years where abatement is more expensive.

4. Results

4.1. European electricity sector under a yearly decreasing emission constraint

The model results of the *Default Scenario* give insights into a possibility for the generation capacity development in the European electricity sector until 2050. Fig. 3 shows the development of electricity generation in Europe between 2020 and 2050, in five-year steps, under the given linear CO_2-reduction path to 2% in 2050. Due to high investment costs, no new nuclear power plants are built, and therefore nuclear power generation is reduced over time as older plants reach the end of their technical lifetime. New-built capacities of nuclear power plants have been observed in sensitivity analyses at installation costs starting at 3,000 €/kW and below. As recently observed installation costs have been significantly higher, no new nuclear capacities are expected. Renewables become the dominant electricity source in Europe. In the absence of carbon capture technology due to high costs, lignite and coal are phased out as no new coal capacities emerge. Gas electrification, on the other hand, is expanded until 2035. Although 215 GW of gas-fired capacities are built, their usage declines significantly after 2035, to become a backup technology. Electricity generation from biomass and other sources such as waste and geothermal energy remains nearly constant.

The largest share of the CO_2 abatement is carried by the renewable sources wind (onshore and offshore) and solar PV. In the competition between the renewables, wind dominates, obtaining a share of over 60% in 2050. This share consists of onshore wind generating 1,570 TWh, and offshore wind adding additional 951 TWh. Despite benefiting from the strongest cost degression, solar PV produces "only" 1,070 TWh in 2050; even though not less than 880 GW of solar PV capacities are installed in 2050. The installations of wind are lower with capacities of 740 GW Onshore and 270 GW Offshore.

To accommodate the fluctuation of renewables, a total of 465 GW of storage capacities are built, mainly towards the latter half of the period. These findings fit the analysis by Zerrahn et al. [48]; who also remark that storage capacities especially will not hinder the development of renewable capacities, especially in the coming years. New pumped storage capacities are negligible due to limited new potential in Europe. Therefore, lithium-ion battery storage obtains almost all investments. DSM, although implemented in the model, only plays a marginal role, providing only 3% of the flexibility needed in the system.

Fig. 4 shows the accumulated investments in power generation capacities in the default scenario in France, Spain, the United

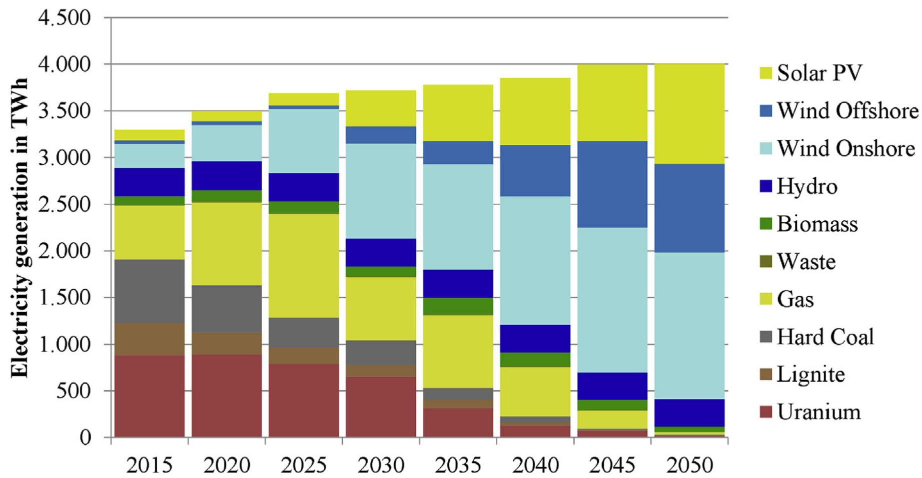

Fig. 3. European electricity generation in the *Default Scenario* 2015–2050.

Kingdom (UK), Germany, Italy, Poland, Greece, and the Netherlands from 2020 until 2050. Aging conventional power plant fleets especially in France, Spain and the UK call for a refurbishment of high shares of their electricity system. Investments in France are highest overall, with 47 GW of new gas power plants, 147 GW onshore and 75 GW offshore wind installations. Investments in solar PV are also above 100 GW; investments in concentrated solar power (CSP) plants appear only in minor quantities in Southern Europe and are aggregated under the solar PV category. In Spain, no new investments in conventional power plants are observed, but onshore wind and solar PV dominate the future electricity generation. This leads to investments into storage technologies of 92 GW. In Germany, onshore and offshore wind power obtain the largest share of investments with 74 GW and 65 GW respectively, whereas the model builds 100 GW of solar PV. Italy shows a different profile due to its climate conditions. Almost only solar PV capacities are built until 2040, followed by some wind, and a little bit of biomass investments. In both countries, the need for storage increases over time.

4.2. Reduced foresight leads to stranded investments

We now compare differences that emerge from different assumptions about the foresight of the decision makers. In the scenario *Reduced Foresight* the myopic foresight, e.g. a reduced vision of future CO_2 abatement needs, leads to a different investment strategy as future long-term decarbonization targets are not considered. This provides insights into possible developments of the power plant portfolio in case the overall investment decision making is not driven by a belief in further decarbonization in the future. This leads to significantly higher investments in carbon fuel capacities. Fig. 5 shows the differences in investments between the *Reduced Foresight* scenario, compared to the *Default Scenario*. In the years 2020 and 2025, the investments in gas capacities are similar to the default scenario. But in 2030 and 2035 additional 56 GW and 59 GW are added to the system, which is 22 GW respective 53 GW higher than in the default scenario. These investments occur mainly in the UK (15 GW), France (14 GW), Spain (7 GW), and Germany (6 GW). In 2035, the investment structure of the *Default Scenario* has shifted to a mostly storage and renewables-based one, whereas investments into gas capacities remain stable until 2035 in the *Reduced Foresight* scenario. Afterwards no additional investments take place. No investments into new lignite or coal-fired power plants occur in any of the scenarios. The majority of these additional investments are possibly "stranded" as they would not have been built under full anticipation of the future emissions constraints. As gas-fired power plants have a lower CO_2 emission per kilowatt-hours (kWh) than coal-fired plants, the gas fired plants are not stranded per se, but shift the electricity generation from coal towards gas. Especially run times of carbon-intensive lignite and coal power plants are substituted by these additional gas power units. The average full load hours of coal-fired power plants are consequently decreased by more than 1.000 h in between 2030 and 2040. Lignite-fired power plants even observe a drop of 33%, compared to the *Default Scenario*, to less than 4000 full load hours in 2035. This change in timing and structure of investments influences the resulting CO_2 emissions.

4.3. Emissions are shifted from coal towards gas

In Fig. 6, the CO_2-emissions over time by fuel are depicted for the default and the reduced foresight scenarios, as well as the difference in emissions induced by the reduced model foresight. In the default setting, emissions from hard coal and lignite decrease faster than emissions from gas, which even increase until 2025. From 2035 onward, overall CO_2 emissions from coal are overtaken by gas, which is from then onwards the largest source of CO_2-emissions. In 2050, the remaining 19 Mt of CO_2 almost exclusively originate from gas power plants.

When comparing the CO_2-emissions in the reduced foresight scenario to the default scenario the aforementioned larger investments into gas fired power plants become also visible. Especially in 2030 these power plants are replacing electricity production from hard coal and lignite power plants and hence the CO_2-emissions are also replaced. In the course of time, the difference between the emissions in both scenarios is reducing due to the tightening of the CO_2-emissions limits. Already by 2045 there is no more difference as the gas fired power plants which were build 2030 are not used anymore and can be considered stranded.

We now compare the results of the *Default Scenario* with those of the *Emission Budget* scenario, where the decision maker is free to allocate the total emission budget (here: about 22.5 bn. t CO_2) over the entire period. Fig. 7 shows the CO_2 emissions in the scenario with an emission budget. Clearly, the control of the full budget leads to a sharp reduction of emissions in the early period (2020–2030), where emissions are about 170 Mt lower than in the default scenario. On the contrary, in 2040 and 2045, emissions under the budget approach increase beyond the default scenario.

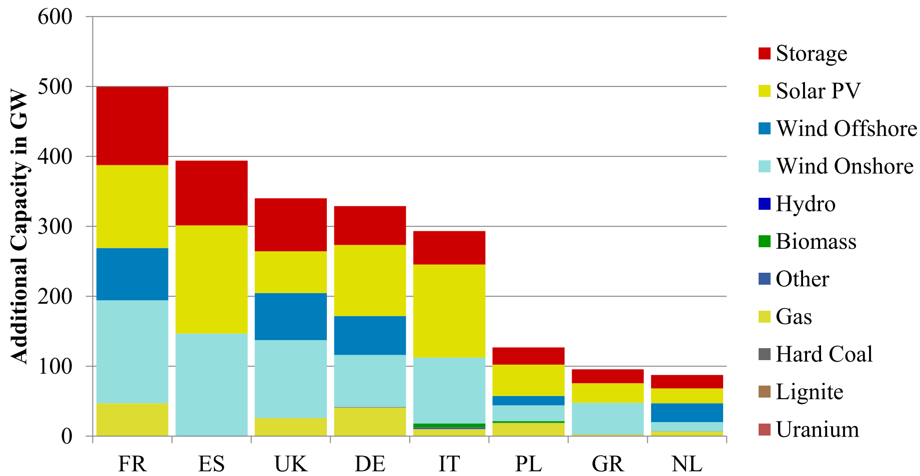

Fig. 4. Accumulated investments in generation capacities in the *Default Scenario* in selected countries from 2020 to 2050.

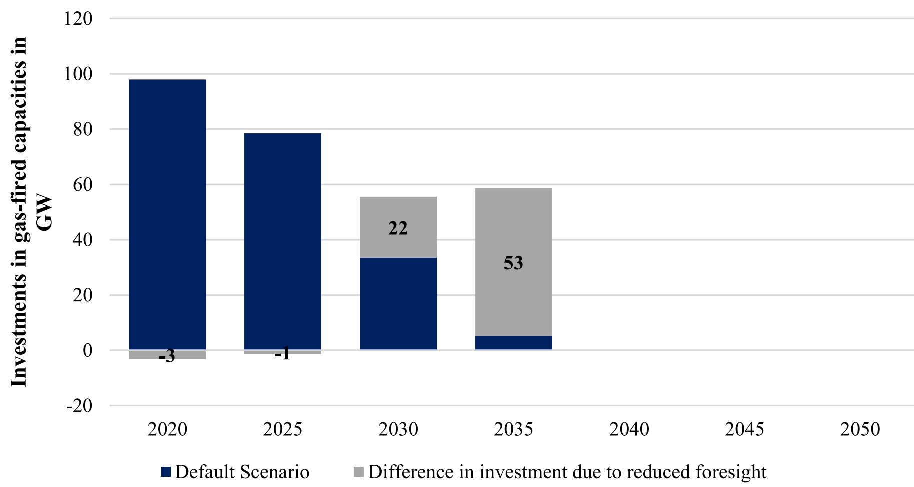

Fig. 5. Investment differences for gas power plants in *Reduced Foresight* scenario vs. *Default Scenario* from 2020 to 2050 in Europe.

Overall system costs over the entire period can be reduced by about 1% due to this shift which amounts to about 1.2 bn € per year for the entire model region. One interpretation of this result is that the new degrees of freedom invite the decision maker to use “low hanging fruits” of abatement earlier, mainly by using existing gas capacities instead of coal and lignite units. This strategy allows for additional emissions, primarily used by gas plants, towards the end of the modeled period.

5. Discussion

5.1. Operating a low-carbon electricity system in 2050

Can a largely renewables-based electricity system, that dynELMOD foresees as the lowest-cost solution for decarbonization, deliver secure electricity? Previously, it was considered that intermittent renewables needed to be balanced by conventional capacities, mainly gas. With the cost degression of both renewable energy and storage capacities, and under a strict carbon constraint, the renewables-gas combination is becoming much less attractive. This section looks at the concrete hour-to-hour functioning of the electricity system and specifically addresses the operation in different European countries using Germany and Italy as examples. Aside from pure electricity generation aspects, also stability of the system and the use of ancillary services with rising shares of renewables becomes important. Lorenz [49] estimates that balancing services can be provided in decarbonized electricity systems at current cost levels if technical and regulatory boundary conditions enable participation of renewables. It is shown that RES participation in balancing provision is mainly important for negative reserves, while storages play an important role for the provision of positive reserves. However, only for very few occasions, additional storage investments are required for balancing reserve provision, as most of the time there are sufficient storage capacities available in the electricity system. In order to keep cost at current levels a dynamic reserve sizing horizon is paramount. Apart from the sizing horizon, storage capacity withholding duration and additional balancing demand from RES are the main driver of balancing costs in 2050.

Fig. 8 shows the hour-to-hour functioning of the German electricity system in the default scenario. The two depicted weeks in early February 2050 are the most critical period in the year regarding demand peaks as well as low solar PV availability and intermittent periods of low wind in-feed as well. Given the investment program sketched out above, wind is clearly the dominant source of supply and delivers 47% of total electricity in that two-week period. Both wind and solar PV are intermittent and have moments where little of it is available, such as around the

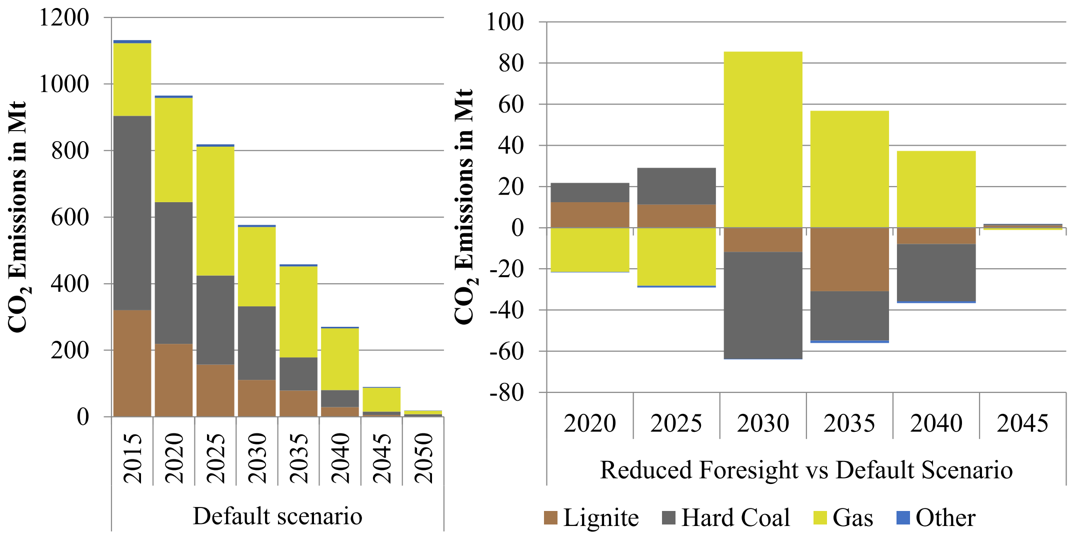

Fig. 6. CO_2 emissions by fuel and scenario.

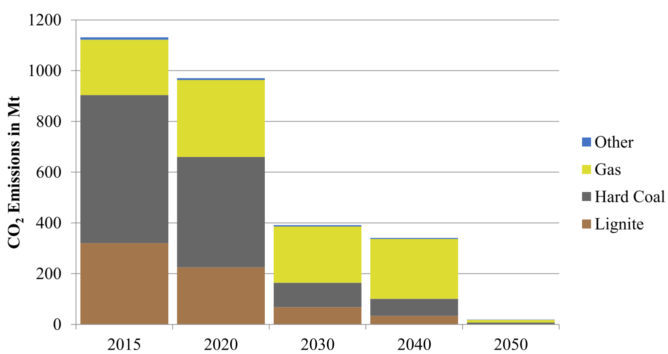

Fig. 7. CO_2 emissions in the "Emission Budget" scenario (2020–2050) in ten-year steps.

model-hour 953, that – in addition to electricity trade, i.e. imports – significant amounts of storage are necessary. These storages are charged at times of high renewable availability or low demand. Between 2020 and 2050, 56 GW of storage capacity have been built. Fig. 8 also shows how the combination of storage and trade assures a secure supply of electricity even in the most critical hours of the year. Therefore, points at which the system is in an inadequate configuration do not occur in any model hour. The imports for Germany come in decreasing order from Denmark, Switzerland, the Netherlands, France, and Austria. The balance with Sweden and Poland is roughly zero. At the same time on average 960 MWh are exported to the Czech Republic. As dynELMOD is a model with an hourly resolution, ramping constraints can only apply to a subset of technologies such as lignite power plants. Gas capacities can ramp to their full capacity within a single hour. This is visible in Fig. 8, where gas capacities show high ramping rates. As the electricity system is almost fully decarbonized in 2050, the electricity supply of gas capacities is limited throughout the year.

Fig. 9 presents a similar exercise for Italy, also in the time-frame of the first two weeks of February for the default scenario. The dispatch of generation technologies in Italy is shaped by wind in-feed as well as solar PV availability which during the day often exceeds the demand. During these hours, storage capacities are charged to release the power during the evening hours. Italy also intermittently relies on imports, mainly from France, Switzerland, and Greece.

5.2. Costs and prices to 2050

The rapid sector transformation leads to substantial investments into a different power generation and storage portfolio compared to today's outset. The costs associated with this transformation and the resulting average electricity generation costs are discussed in this section. Fig. 10 shows the composition of total system costs for the default scenario, about €$_{2015}$ 4,900 bn., composed of initially approximately equal shares for variable costs, investment costs, and operation & maintenance costs. Over time variable generation costs decrease as the system shifts to a more renewables based dispatch. Even though it constitutes a crucial element in the generation mix, the costs for storage make up only about 3% of total system costs. Also, investments in the electricity grid infrastructure only contribute to 1.3% of the total costs.

Dividing the system costs by electricity generation provides an aggregate average cost of supplying Europe with electricity. Fig. 10 also shows the development of average costs for the period 2020–2050, which shows a decreasing trend: from 52 €/MWh in 2020, mainly based on fossil fuels, until 2050, where an average cost of 27 €/MWh is reached.

Last but still not least we take a look at the implicit CO_2-prices that the model renders as the shadow price on the carbon constraint. Not surprisingly, the reduction of the available CO_2 emissions in the *Default Scenario* leads to an increase in the implicit CO_2 price: from 32 €/t (2020) to 177 €/t (2050). The price development of the *Reduced Foresight* is comparable to the default scenario, here the price increase occurs at a later stage between 2045 and 2050. For the emission budget, no yearly values, but a price spanning the entire model period is available. At about 34 €/t it reflects the shadow price of an additional ton of CO_2 at any point during the period from 2015 to 2050.

5.3. Realization and development risks of large-scale electricity storage until 2050

In general, a positive correlation between high shares of renewables and storage capacities can be found across the literature.

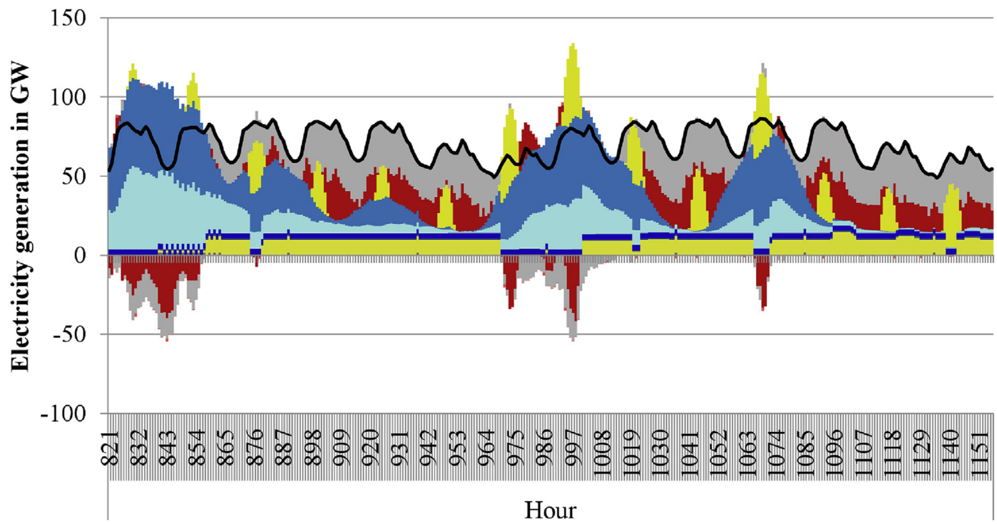

Fig. 8. Hour-to-hour operation of the German electricity system in 2050 (first two weeks of February) for the default scenario.

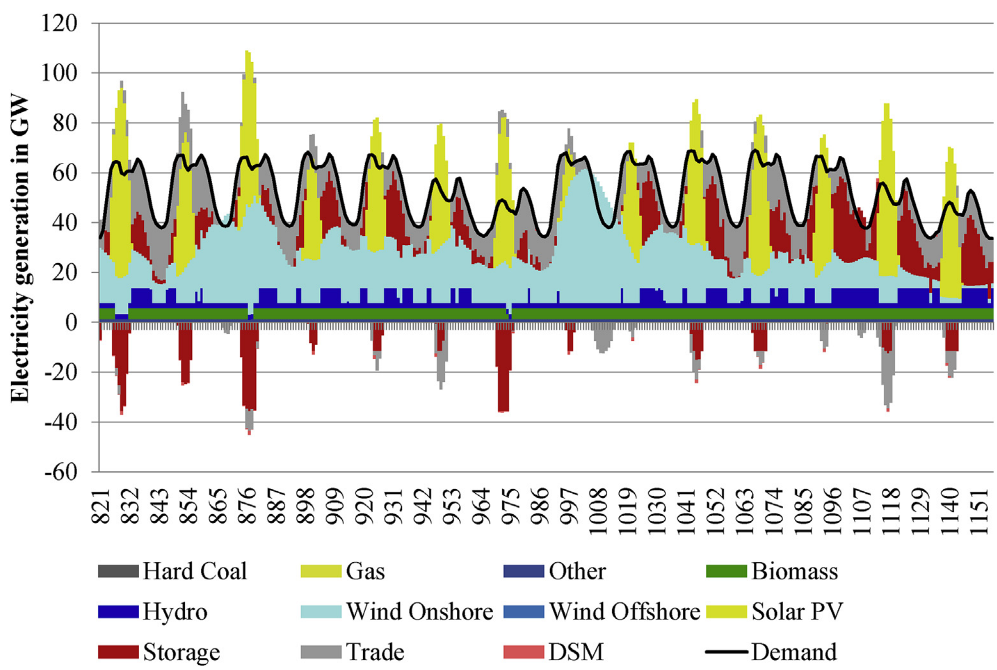

Fig. 9. Hour-to-hour operation of the Italian electricity system in 2050 (first two weeks of February) for the default scenario.

Schill and Zerrahn [50] highlight in addition that the relevance of power storages is even higher, if other flexibility Model and Data options are less developed. Our model results in overall storage with capacities between 253 GW (90% decarbonization) and 518 GW (100% decarbonization) by 2050 in Europe. These volumes are in the range of estimations for other low carbon scenarios that meet the agreed on climate targets of the European Union. Scenarios by the European Commission [51] result in electricity storage of 250–450 TWh and overall storage capacities in the range of 400–800 GW (including pumped hydro, batteries, hydrogen, PtG, and PtL). Similar figures are derived by Hainsch et al. [52] of around 750 GW or even slightly above 1,000 GW in the case of Bussar et al. [53]. Other experts, e.g. Cebulla et al. [54]; project lower required additional amounts of electricity storage in the range of 100–300 GW. Across all analyzed scenarios, it becomes obvious that extensive investment for the storage of electricity and energy in general is needed to enable the ongoing energy transition. The following section therefore elaborates in more detail additional insecurities to be taken into consideration when projecting future storage investments.

The differences between the estimations can be explained through different scope (i.a. different climate targets, included sectors, analyzed time periods, or regions), technology assumptions (i.a. technology or fuel costs, weather conditions, siting possibilities especially for hydro storage including public acceptance issues), and level of detail (i.a. time resolution, storage technologies, efficiency improvements, demand flexibilities and customer behavior). Also, most models do not try to forecast future storage installments but should be interpreted as proposals for a low cost pathway direction. Especially, if the interaction with the electricity grid [55,56] or synergies with balancing are taken into account [57], the amount of storage is lower. Also, a negative correlation between storage and

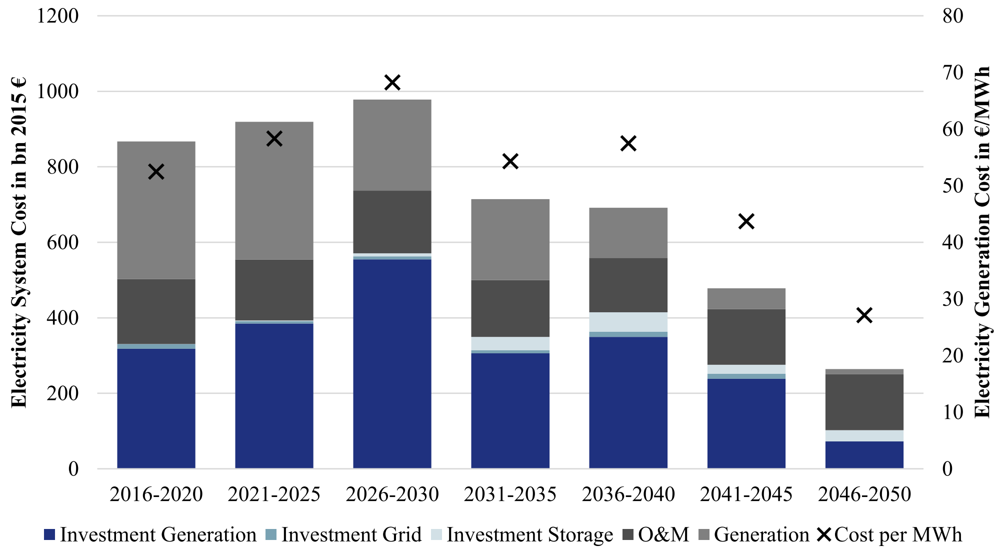

Fig. 10. Overall electricity system costs (2020–2050), by segment.

trade capacities can be observed, showcasing the power grid as another form of storage [52].

The required storage capacities strongly increase in most scenarios if the share of renewables surpasses 80% and gets in the range of 100%. Needed backup power in these latter cases is in the order of the peak load [11]. Including longer periods of low renewable energy generation (see section 5.1) furthermore increases the need for storage. Weitemeyer et al. [58] therefore in particular stresses the need for seasonal storages in such system configurations. A significant share of the necessary storage capacity could be provided through sector coupling [8] which is not included in this modeling approach. With possibilities of flexibly dispatching the batteries of electric vehicles [59,60], the flexibility of power to heat systems [61], further power-to-gas options [62,63] could possibly reduce necessary storage capacity significantly. Given the focus on the electricity sector alone, our model results therefore report storage capacities leaning to the higher end of the spectrum in the literature especially in scenarios with high levels of decarbonization.

In order to reach the designated storage capacities in 2050, in the coming 30 years major improvements in storage technologies are needed for fast built-out especially in the period from 2040 to 2050. Assuming such a positive development involves technical, economical and geopolitical uncertainties which need to be considered when evaluating a highly renewable and storage-dependent transformation pathway. For electricity storage technologies, the development of future storage systems depends on further technological advancements in combination with cost decreases. Kittner et al. [64] show that – given a technological advancement extrapolated from historical technological development – renewables and storage can become a competitive combination compared to fossil alternatives. Still, uncertainties persist if necessary technological development can be achieved to make large-scale storage technology viable.

When assuming a large build-out of possibly few storage technologies the availability of necessary resources must be considered [65,66]. Next to conventional resources like steel or copper, which are also needed for other renewable generation technologies [67,68], especially battery storages require materials (e.g. rare earths) which are limited and not spread equally over the world [65,69]. A recent report by SRU [70] shows that the current extraction rate for the critical materials used in battery storage needs to increase five-fold to achieve the required levels. Even though, an increase in the extraction rates is assumed to be a solvable problem increasing efficiency and recycling materials is essential for enabling a transition towards a more sustainable energy system.

6. Conclusion

Enabling a decarbonization of the electricity sector is crucial for keeping global temperature rise under 2° C, as agreed on at the climate conference in Paris, as mitigating emissions in other sectors is more difficult and costlier. No investments in new hard coal or lignite fueled power plants are observed in any scenario. Incorporating the climate targets makes the investment into any additional conventional capacity uneconomic from 2025 onwards, resulting in a coal and gas phase-out in the 2040s.

However, international consensus on how to achieve a decarbonization of the sector is lacking. Electricity generation will undergo substantial structural change over the next three decades, and developments in Europe, where strict carbon restrictions are likely to be imposed, are a particularly interesting case. This paper presents different pathways for the decarbonization of the European electricity sector in 2050 relying on a very detailed model of electricity generation, transmission, and consumption, called dynELMOD.

The model is applied to different foresight assumptions. These results quantify the advantage of a structured energy transition pathway instead of potentially short-sighted decisions. Limited foresight results in stranded investments of 75 GW of gas-capacities in the 2030s. The amount of stranded investments is small compared to the overall installed capacities, but a robust result across sensitivities. Using a CO_2 budgetary approach, on the other hand, leads to an even sharper emission reduction in the early periods before 2030, reducing overall costs by 1%. We find that in all scenarios renewables carry the major burden of decarbonization, other technologies such as nuclear power (3rd or 4th generation) and carbon capture appear to be to costly to compete.

Transforming the electricity system towards an almost full (98%) decarbonization by 2050 changes the overall generation structure substantially. The accompanying total electricity generation cost shows a downward trend after reaching its highest point in 2025, to arrive at a minimum of 27€/MWh in 2050 in the default scenario.

Across all scenarios costs in 2050 range between 27€/MW and 32€/MWh and therefore below levels of 2017.

Further research is needed to address the diffusion process of new technologies, mainly renewables and storage: we have assumed the emerging technologies to be available in all countries, and at identical, rather low costs. However, these assumptions may not be provided in practice. Another important aspect is the future use of nuclear energy. While electricity from nuclear energy is clearly not economic, some countries are likely to pursue the nuclear route, for other reasons, and this should be reflected in the specific scenario runs. Finally, the role of electricity transmission infrastructure needs to be critically reviewed as a simplified representation is used to reduce computational complexity.

Acknowledgments

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Appendix A. dynELMOD model formulation

The model dynELMOD is described in this section.[2] It includes two decision levels, the dispatch and the investment in transmission and generation. These levels are reduced to one level assuming perfect competition and a central planer that minimizes total system cost. The model is formulated as a linear program (LP) consisting of equations (A.1) to (A.34) in GAMS. It is solved using commercially available solvers such as GUROBI or CPLEX.

Objective function. The objective of total system cost *cost* (A.1) include variable cost for generation $cost^{gen}$ (A.2), investment cost for new built generation $cost^{inv}$ (A.3), fixed operation and maintenance cost for existing and new built generation capacity $cost^{cap}$ (A.4), and investment cost for network expansion $cost^{line}$ (A.5). The nomenclature for all sets, variables and parameters can be found in Section Appendix B. Variable cost for existing capacity are considered on a block level, whereas new built capacities are aggregated by technology and depend on the commissioning date of the respective generation capacity. In order to ensure a consistent representation of the investment cost, annuities are calculated using a discount rate I^i. Furthermore, all cost components are discounted with the interest rate I^d which results in the discount factor DF_y.

$$\min cost = cost^{gen} + cost^{inv} + cost^{cap} + cost^{line} \tag{A.1}$$

$$\begin{aligned} cost^{gen} = & \sum_{co,i,t,y,p} Cvar_{p,co,i,y} * g^{existing}_{p,co,i,t,y} * DF_y \\ & + \sum_{co,i,t,y,yy,yy\leq y} Cvar^{newbuilt}_{co,i,y,yy} * g^{newbuilt}_{co,i,t,y,yy} * DF_y \\ & + \sum_{co,i,t,y,yy} Cload_{co,i,y} * \left(g^{up}_{co,i,t,y} + g^{down}_{co,i,t,y} \right) * DF_y \end{aligned} \tag{A.2}$$

$$\begin{aligned} cost^{inv} = & \sum_{co,i,y,yy,yy\leq y} Cinv_{i,yy} * inv^{cap}_{co,i,yy} * DF_y \\ & + \sum_{co,i,y,yy,yy\leq y} Cinv^{stor}_{i,yy} * inv^{stor}_{co,i,yy} * DF_y \end{aligned} \tag{A.3}$$

$$cost^{cap} = \sum_{co,i,y} Cfix_{co,i,y} * \left(\sum_p G^{max}_{p,co,i,y} + \sum_{yy} inv^{cap}_{co,i,yy} + inv^{stor}_{co,i,yy} \right) * DF_y \tag{A.4}$$

$$cost^{line} = \sum_{yy,co,coo} Cline_{co,i,y} * 0.5 * inv^{line}_{yy,co,cco} * DF_{yy} \tag{A.5}$$

The investment cost in dynELMOD are accounted for on an annuity basis. When investments occur, not the entire cost is accounted for in the year of investment, but the to-be-paid annuities are tracked over the economic life time of the investment, also taking into account the remaining model periods to ensure no distortion due to the end of the model horizon. The tracking of the remaining periods is not shown for clarity.

All equations above are also scaled depending on the length of the time frame t to represent yearly values, if necessary. This ensures a distortion-free representation of all cost-components regardless of the time frame included in the model. Furthermore, the equations (A.2) to (A.5) are scaled with a scaling parameter to ensure similar variable magnitude orders. This helps the solver to achieve fast solution times. In (A.5) the line expansion is multiplied by 0.5 as the investment is tracked on "both sides" of the line.

Market clearing. The market is cleared under the constraint that generation has to equal load at all times including imports or exports via the high-voltage alternating current (HVAC) or high-voltage direct current (HVDC) transmission network (A.6). Depending on the grid approach, the equation (A.6) contains either the variables to represent the network using a PTDF and HVDC-lines or, in the case of the net transfer capacity (NTC)-Approach contains the flow variable between countries.

$$\begin{aligned} 0 = \; & Q_{co,t,y} - \sum_i g_{co,i,t,y} \\ & \left. \begin{aligned} & + ni_{co,t,y} \\ & + \sum_{cco} dcflow_{co,cco,t,y} \\ & - \sum_{cco} dcflow_{cco,co,t,y} \end{aligned} \right\} \text{Flow} - \text{based approach} \quad \forall y, co, t \\ & \left. + \sum_{cco} flow_{cco,co,t,y} \right\} \text{NTC approach} \end{aligned} \tag{A.6}$$

Generation restrictions. The conventional generation is differentiated into generation of existing and newbuilt capacity and is constrained by the installed capacity, taking into account an average technology specific availability as defined in (A.8) and (A.9). For non-dispatchable technologies availability is defined for every hour and is calculated during the time series scaling procedure described in Gerbaulet and Lorenz [37]. Together with the loading and release from the storage the generation from newbuilt and existing capacities is summed up to a joint generation parameter in equation (A.7). The variable representing the generation from new built capacity is additionally dependent on a second set of years which represent the year when the capacity has been built. The same holds for the variable representing the newbuilt capacity. Equation (A.10) defines the generation of renewable capacities. Here the generation can be less than the available capacity in each hour, without accumulating curtailment cost in the system.

$$\begin{aligned} g_{co,disp,t,y} = & \sum_p g^{existing}_{p,co,disp,t,y} + \sum_{yy\leq y} g^{newbuilt}_{co,disp,t,y,yy} \\ & + stor^{Release}_{co,i,t,y} - stor^{loading}_{co,i,t,y} \quad \forall co, disp, t, y \end{aligned} \tag{A.7}$$

[2] This section is based on Gerbaulet and Lorenz [37].

$$g^{existing}_{p,co,disp,t,y} \leq Ava_{co,disp,y} * G^{max}_{p,co,disp,y} \quad \forall p, co, disp, t, y \tag{A.8}$$

$$g^{newbuilt}_{co,disp,t,y,yy} \leq Ava_{co,disp,y} * inv^{cap}_{co,disp,yy} \quad \forall co, disp, t, y, yy \tag{A.9}$$

$$\begin{aligned} g_{co,ndisp,t,y} \leq & \sum_{yy \leq y} ResAva^{newbuilt}_{co,t,ndisp,yy} * inv^{cap}_{co,ndisp,yy} \\ + & \sum_{p} ResAva^{existing}_{co,t,ndisp} * G^{max}_{p,co,ndisp,y} \quad \forall co, ndisp, t, y \end{aligned} \tag{A.10}$$

Fuel restriction. Some fuels (e.g. biomass) face a limitation on their yearly consumption. Therefore the total energy output from this fuel is restricted as defined in (A.11). In scenarios where multiple technologies compete for a fuel (e.g. Biomass and Biomass with CCTS) it also determines an efficient endogenous share between these technologies.

$$\sum_{p,i,t} \frac{g^{existing}_{p,co,i,t,y}}{\eta^{existing}_{p,co,i,y}} + \sum_{i,t,yy \leq y} \frac{g^{newbuilt}_{co,i,t,y,yy}}{\eta^{newbuilt}_{co,disp,yy}} \leq \quad Gen^{max}_{co,f,y} \quad \forall co, f, y \tag{A.11}$$

Combined heat and power. The combined heat and power (CHP) constraint is implemented as a minimum run constraint that depends on the type of power plant as well as the outside temperature. Thus $g^{existing}_{p,co,i,t,y}$ has to be equal or greater than $G^{min\_chp}_{p,co,i,t}$. The constraint is only valid for existing power plants as it would have unintended side-effects when also applied to new built technologies. Due to the minimum generation constraint the new built capacities would have to produce and hence emit CO_2. This could potentially violate the emission constraint and thus investment into fossil power plants would not be possible.

$$g^{existing}_{p,co,i,t,y} \geq G^{min\_chp}_{p,co,i,t} \quad \forall co, i, t, y \tag{A.12}$$

Investment restrictions. Equations (A.14) and (A.15) limit the maximum investment in conventional generation and storage technologies. The parameter $G^{max\_inv}_{co,c,y}$ is scaled according to the number of years between the time steps to account for a yearly investment limit.

$$g^{instcap}_{co,i,y} = \sum_{p} G^{max}_{p,co,i,y} + Storage^{maxrelease}_{co,i,y} + \sum_{yy \leq y} inv^{cap}_{co,i,yy} \quad \forall co, i, y \tag{A.13}$$

$$g^{instcap}_{co,i,y} \leq G^{Max\_installed}_{co,i,y} \quad \forall co, i, y \tag{A.14}$$

$$\sum_{co,i} inv^{cap}_{co,i,y} \leq G^{max\_inv}_{co,i,y} \quad \forall co, i, y \tag{A.15}$$

Ramping. In the model, ramping of technologies is implemented in two ways: On the one hand, for some technology types, the ramping speed is limited. Here equations (A.16) and (A.17) limit the relative rate of generation output change per hour. As this model is applied on an hourly basis, this limitation only applies to a subset of generation technologies (e.g. Lignite). Further, to represent a more economic dispatch behavior regarding ramping, wear and tear of the materials within the power plant as well as additional fuel consumption for ramping are represented using ramping costs. The linear model cannot contain binary or integer variables. Thus, the assumed costs for ramping are slightly higher than in a unit commitment model to account for this model characteristic. The load change cost of ramping does not need to be tracked for each p, as the ramping speeds are tracked on a technology level (A.18).

$$g^{up}_{co,c,t,y} \leq R^{up}_{i,y} * \sum_{p} G^{max}_{p,co,i,y} + \sum_{yy \leq y} R^{up}_{i,yy} * inv^{cap}_{co,i,yy} \quad \forall co, i, t, y \tag{A.16}$$

$$g^{down}_{co,i,t,y} \leq R^{down}_{i,y} * \sum_{p} G^{max}_{p,co,i,y} + \sum_{yy \leq y} R^{down}_{i,yy} * inv^{cap}_{co,i,yy} \quad \forall co, i, t, y \tag{A.17}$$

$$g^{up}_{co,i,t,y} - g^{down}_{co,i,t,y} = g_{co,i,t,y} - g_{co,i,t-1,y} \quad \forall co, i, t, y \tag{A.18}$$

Emission restrictions. In the standard setting, a yearly CO_2 emission limit spanning the entire electricity sector is implemented. The amount of available emissions represents the amount available to the electricity sector. In case a total emission budget spanning the entire model horizon is in place, the emission limit of the first and last model period will still be active. On the one hand, the power plant dispatch in the starting period – where no investments take place – should not be affected by future decisions. On the other hand, the final emission target is also adhered to.

$$\begin{aligned} Emissionlimit_y \geq & \sum_{p,co,i,t} g^{existing}_{p,co,i,t,y} CarbonRatio^{emission}_{p,co,i,y} \\ + & \sum_{co,i,t,yy \leq y} g^{newbuilt}_{co,i,t,ys,yy} CarbonRatio^{emission,new}_{co,i,yy} \quad \forall y \end{aligned} \tag{A.19}$$

$$\begin{aligned} \sum_{y} Emissionlimit_y \geq & \sum_{y,p,co,i,t} g^{existing}_{p,co,i,t,y} CarbonRatio^{emission}_{p,co,i,y} \\ + & \sum_{y,co,i,t,yy \leq y} g^{newbuilt}_{co,i,t,ys,yy} CarbonRatio^{emission,new}_{co,i,yy} \end{aligned} \tag{A.20}$$

CCTS. As carbon capture and storage plans are implemented as normal generation technologies, additional constraints account for the total amount of CO_2 that can be stored. As we assume that no large-scale carbon transport infrastructure emerges in the future, the captured emissions need to be stored locally within each country. This leads to country-sharp CCTS constraints that are valid for all model periods.

$$\begin{aligned} CCTSStor^{Capacity}_{co} \geq & \sum_{y,p,co,i,t} g^{existing}_{p,co,i,t,y} CarbonRatio^{sequestration}_{p,co,i,y} \\ + & \sum_{y,co,i,t,yy \leq y} g^{newbuilt}_{co,i,t,ys,yy} CarbonRatio^{sequestration,new}_{co,i,yy} \quad \forall co \end{aligned} \tag{A.21}$$

Storage. The operation of storages is constrained in equations (A.22 to A.26). On the one hand the storage operation is limited by the installed loading and release capacity which can be increased by the model (A.22, A.23). On the other hand the release and loading is constrained by the current storage level defined in equation (A.24).[3] The storage level in return is limited by minimum and maximum storage levels that can be increased by the model independently from turbine and pump capacity (A.25, A.26). Therefore the model can decide upon the optimal energy to power ratio (E/P-Ratio).

[3] The storage level in the first modeled hour must equal the storage level in the last modeled hour, to ensure continuity at the end and the start of each year.

$$stor^{release}_{co,s,t,y} \leq Ava_{co,s,y}*Storage^{maxrelease}_{co,s,y} + Ava_{co,s,y}*\sum_{yy\leq y} inv^{cap}_{co,s,yy} \quad \forall co,s,t,y \tag{A.22}$$

$$stor^{loading}_{co,s,t,y} \leq Ava_{co,s,y}*Storage^{maxloading}_{co,S,y} + Ava_{co,s,y}*\sum_{yy\leq y} inv^{cap}_{co,s,yy} \quad \forall co,s,t,y \tag{A.23}$$

$$stor^{level}_{co,s,t,y} = stor^{level}_{co,s,t-1,y} - stor^{Release}_{co,s,t,y} + \eta^{storage}_{co,s,y}*stor^{loading}_{co,s,t,y} + Inflow_{co,s,y,t} \quad \forall co,s,t,y \tag{A.24}$$

$$stor^{level}_{co,s,t,y} \leq Storage^{maxlevel}_{co,s,y} + \sum_{yy\leq y} inv^{stor}_{co,i,yy} \quad \forall co,s,t,y \tag{A.25}$$

$$stor^{level}_{co,s,t,y} \geq Storage^{minlevel}_{co,s,y} \quad \forall co,s,t,y \tag{A.26}$$

Demand-side-management. DSM is also expected to increase the flexibility in the electricity system. In dynELMOD we focus on DSM where the total demand remains constant overall but can be delayed several hours. In order to keep the model structure simple, we implement DSM as a storage technology. In addition to the standard storage equations, DSM requires further constraints. Depending on the DSM technology models, usage cost occur, and the maximum hours of load shifting need to be tracked. We implement DSM based on a formulation by Göransson et al. [71]. As DSM uses the storage equations framework as a basis, most of the implementation is reversed compared to the formulation by Göransson et al. [71]. An alternative implementation by Zerrahn and Schill [72] would enable a slightly more accurate tracking of demand-shifts, but the computational overhead was too high to include this formulation in the model. In addition to the equations for normal storages DSM are restricted by the equations (A.27–A.28). The $stor^{level}_{co,dsm,t,y}$ for all DSM technologies is also tracked to be equal at the beginning and end of the model period.

$$\sum_{tt,tt+dsmratio\geq t,tt\leq t} stor^{Release}_{co,dsm,tt,y} \geq Storage^{maxlevel}_{co,dsm,y} + \sum_{yy\leq y} inv^{stor}_{co,dsm,yy} - stor^{level}_{co,dsm,t,y} \quad \forall co,dsm,t,y \tag{A.27}$$

$$\sum_{tt,tt\geq t,tt-dsmratio\leq t} stor^{loading}_{co,dsm,tt,y} \geq Storage^{maxlevel}_{co,dsm,y} + \sum_{yy\leq y} inv^{stor}_{co,dsm,yy} - stor^{level}_{co,dsm,t,y} \quad \forall co,dsm,t,y \tag{A.28}$$

Network restrictions. When using the NTC approach, the flow between countries is defined in equation (A.29). The flow between two countries is limited by the available NTC, that can be increased by the model in (A.30) and (A.31) through investments in network infrastructure.

$$flow_{co,cco,t,y} = -flow_{cco,co,t,y} \quad \forall co,cco,t,y \tag{A.29}$$

$$flow_{co,cco,t,y} \leq NTC_{co,cco} + \sum_{yy\leq y} inv^{line}_{yy,co,cco} \quad \forall co,cco,t,y \tag{A.30}$$

$$flow_{co,cco,t,y} \geq -NTC_{co,cco} - \sum_{yy\leq y} inv^{line}_{yy,co,cco} \quad \forall co,cco,t,y \tag{A.31}$$

When using the PTDF approach a more complex framework is required. For load flow calculations we use a country-sharp PTDF matrix of the European high-voltage AC grid which is relevant in (A.32). DC-interconnectors are incorporated as well (A.33). Equation (A.34) enforces symmetrical line expansion between countries.

$$\sum_{ccco} PTDF_{co,cco,ccco}*ni_{ccco,t,y} \leq P^{max}_{co,cco} + \sum_{yy\leq y} inv^{line}_{yy,co,cco} \quad \forall co,cco,t,y \tag{A.32}$$

$$dcflow_{co,cco,t,y} \leq Hvdc^{max}_{co,cco} + \sum_{yy\leq y} inv^{line}_{yy,co,cco} \quad \forall co,cco,t,y \tag{A.33}$$

$$inv^{line}_{y,co,cco} = inv^{line}_{y,cco,co} \quad \forall y,co,cco \tag{A.34}$$

Foresight reduction. dynELMOD can be adjusted regarding the "planners foresight" as shown in this paper to be able to answer a wide range of questions.

In the standard setting, the model is solved for all years in the model with perfect foresight over all optimization periods. To mimic a more myopic behavior, the foresight of the model regarding the upcoming periods can be reduced to limit the anticipation of the planner. The model then assumes that the overall boundary conditions remain constant after the model optimization period ends.

This setting requires iterating over the set of all years included in the model, as the horizon progresses over time. Assuming the foresight period is set to 10 years, the first optimization iteration covers the time steps 2015,[4] 2020, and 2025. In the next step the investments of the year 2015 are fixed. Then the year 2030 is added to the time horizon and the optimization is repeated. Next, the optimizations of 2025 are fixed and the process repeats until the time horizon reaches the final time step.

Appendix B. dynELMOD model nomenclature

Table B.1
Sets in dynELMOD.

Sets	
p	Power plant
f	Fuel
i	Generation technology
$c(i)$	Conventional technology
$disp(i)$	Dispatchable technology
$ndisp(i)$	Non-dispatchable technology
$s(i)$	Storage technology
$dsm(i)$	DSM technology
t,tt	Hour
y	Calculation Year
yy	Investment Year
$co,cco,ccco$	Country

[4] In the actual model formulation, 2015 is only included as a starting year, the power plant portfolio is not optimized for this year.

Table B 2
Variables in dynELMOD.

Variables	
$cost$	Objective value: total cost
$cost^{gen}$	Variable generation cost
$cost^{inv}$	Investment in generation capacity
$cost^{cap}$	Fixed generation capacity cost
$cost^{line}$	Line expansion cost
$g_{co,i,t,y}$	Sum of existing and newbuilt electricity generation
$g^{existing}_{co,i,t,y}$	Generation of existing technology
$g^{newbuilt}_{co,i,t,y,yy}$	Generation of new built technology
$g^{up}_{co,i,t,y}$	Upward generation
$g^{down}_{co,i,t,y}$	Downward generation
$g^{instcap}_{co,i,y}$	Installed generation capacity
$inv^{cap}_{co,i,yy}$	New generation capacity
$inv^{stor}_{co,i,yy}$	New storage capacity
$inv^{line}_{y,co,cco}$	Grid expansion
$ni_{co,t,y}$	Net input from or to network in country
$dcflow_{co,cco,t,y}$	HVDC flow between countries
$flow_{co,cco,t,y}$	Flow between countries in NTC approach
$stor^{level}_{co,i,t,y}$	Storage level
$stor^{loading}_{co,i,t,y}$	Storage loading
$stor^{release}_{co,i,t,y}$	Storage release

Table B 3
Parameters in dynELMOD.

Parameters		
$Ava_{co,i,y}$	Average annual availability [%]	
$CarbonRatio^{emission,new}_{co,i,yy}$	Carbon emission ratio of newbuilt capacities	
$CarbonRatio^{emission}_{p,co,i,y}$	Carbon emission ratio of existing capacities	
$CarbonRatio^{sequestration,new}_{co,i,yy}$	Carbon sequestration ratio of newbuilt capacities	
$CarbonRatio^{sequestration}_{p,co,i,y}$	Carbon sequestration ratio of existing capacities	
$CCTSStor^{Capacity}_{co}$	CO_2 storage capacity	
$Cfix_{co,i,y}$	Fix generation cost [EUR per MW]	
$Cinv^{stor}_{i,y}$	Annuity of storage investment [EUR per MWh]	
$Cinv_{i,y}$	Annuity of investment [EUR per MW]	
$Cline_{y,co,cco}$	Line expansion cost [EUR per (km and MW)]	
$Cload_{co,i,y}$	Load change cost [EUR per MWh]	
$Cvar^{newbuilt}_{co,i,y,yy}$	Variable cost of new built technology [EUR per MWh]	
$Cvar_{co,i,y}$	Variable cost of existing technology [EUR per MWh]	
DF_y	Discount factor for each year	
$Emissionlimit_y$	Yearly CO_2 emission limit	
$\eta^{existing}_{p,co,i,y}$	Thermal efficiency of existing technology [%]	
$\eta^{newbuilt}_{p,co,i,y}$	Thermal efficiency of newbuilt technology [%]	
$\eta^{storage}_{co,i,y}$	Storage efficiency [%]	
$G^{max\_installed}_{co,i,y}$	Maximum installable capacity [MW]	
$G^{max\_inv}_{co,i,y}$	Maximum investment per time period [MW]	
$G^{max}_{p,co,i,y}$	Maximum generation of existing capacities [MW]	
$G^{min\_CHP}_{p,co,t,i}$	Minimum generation induced by CHP constraint [MW]	
$Gen^{max}_{co,f,y}$	Availability of fuel f [MWh_{th}]	
$HVDC^{max}_{co,cco}$	Maximum existing HVDC transmission capacity [MW]	
$Inflow_{co,s,y,t}$	Inflow into reservoirs or other storages [MW] $NTC_{co,cco}$	NTC between countries
$P^{max}_{co,cco}$	Maximum existing AC transmission capacity [MW]	
$PTDF_{co,cco,ccco}$	Country-sharp power transfer distribution matrix	
$Q_{co,t,y}$	Electricity demand [MWh]	
$R^{down}_{i,y}$	Ramping down [% per hour]	
$R^{up}_{i,y}$	Ramping up [% per hour]	
$ResAva^{existing}_{co,t,i}$	Renewable vailability of existing capacities [%]	
$ResAva^{newbuilt}_{co,t,i,y}$	Renewable vailability of newbuilt capacities [%]	
$Storage^{maxlevel}_{co,i,y}$	Maximum storage level of existing capacities [MWh]	
$Storage^{maxloading}_{co,i,y}$	Maximum storage loading of existing capacities [MW]	
$Storage^{maxrelease}_{co,i,y}$	Maximum storage release of existing capacities [MW]	
$Storage^{minlevel}_{co,i,y}$	Minimum storage level of existing capacities [MWh]	

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.renene.2019.02.099.

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