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MyPyPSA-Ger: Introducing CO2 taxes on a multi-regional myopic roadmap of the German electricity system towards achieving the 1.5 °C target by 2050

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HIGHLIGHTS

- Earlier phase-out of coal is not the best answer to achieve energy transition.
- The 2050 plan and historical RES investments maxima are not enough to reach climate neutrality.
- What is the effect of regional RES limits over Nationwide RES limits.
- Where will be the states in Germany having major RES deployment.
- Myopic optimization reveals new challenges for energy policy.

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ABSTRACT

This paper will introduce the open-source model MyPyPSA-Ger, a myopic optimization model developed to represent the German energy system with a detailed mapping of the electricity sector, on a highly disaggregated level, spatially and temporally, with regional differences and investment limitations. Furthermore, this paper will give new outlooks on the German federal government 2050 emissions goals of the electricity sector to become greenhouse gas neutral by proposing new CO_2 allowance strategies. Moreover, the regional differences in Germany will be discussed, their role and impact on the energy transition, and which regions and states will drive the renewable energy utilization forward.

Following a scenario-based analysis, the results point out the major keystones of the energy transition path from 2020 to 2050. Solar, onshore wind, and gas-fired power plants will play a fundamental role in the future electricity systems. Biomass, run of river, and offshore wind technologies will be utilized in the system as base-load generation technologies. Solar and onshore wind will be installed almost everywhere in Germany. However, due to the nature of Germany's weather and geographical features, the southern and northern regions will play a more important role in the energy transition.

Higher CO_2 allowance costs will help achieve the 1.5-degree-target of the electricity system and will allow for a rapid transition. Moreover, the more expensive, and the earlier the CO_2 tax is applied to the system, the less it will cost for the energy transition, and the more emissions will be saved throughout the transition period. An earlier phase-out of coal power plants is not necessary with high CO_2 taxes, due to the change in power plant's unit commitment, as they prioritize gas before coal power plants. Having moderate to low CO_2 allowance cost or no clear transition policy will be more expensive and the CO_2 budget will be exceeded. Nonetheless, even with no policy, renewables still dominate the energy mix of the future.

However, maintaining the maximum historical installation rates of both national and regional levels, with the current emissions reduction strategy, will not be enough to reach the level of climate-neutral electricity system. Therefore, national and regional installation requirements to achieve the federal government emission reduction goals are determined. Energy strategies and decision makers will have to resolve great challenges in order to stay in line with the 1.5-degree-target.

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1. Introduction

Leaders of the globe drafted in 2015 the Paris Agreement to esteem and encourage the global efforts to mitigate the greenhouse gases (GHG), and a start of a more responsible and effective behaviour toward the global warming and climate change [1]. As a result, Germany published its Climate Action Plan 2050, to lay out different measures with the goal of achieving GHG neutrality by 2050 [2].

Many studies have discussed possible paths to the future European energy system achieving the GHG targets and mitigating their CO_2 emissions [3–8]. TIAM-UCL [9] model studied the implications of various CO_2 reduction targets and actions on the energy system and the emissions prices on a global level. ZENIT [10] model studied a small region in Norway and analysed various compensation methods of CO_2 emissions to reach an emission-free energy system. GTAPINGAMS [11] model examined the economic impact of CO_2 emission price on different participants in a domestic economy in Germany. The TIMES model was used in [12] to study the Chinese power market and the influence of different CO_2 taxes, and proposed an emissions policy to form the future energy structure.

There are several energy system models already available that address different areas of the energy system and the scope that they study, either focusing on a specific region or country level, or an interconnected international level. The models differ mainly in their characteristics, such as model structure and information processing (Top-down, Bottom-up), scenario-based, technologies and degree of innovation/complication, data availability and transparency, modelling perspective, spatiotemporal resolution, accuracy and computational effort, societal level, or type of mathematical model [13,14]. The studies in [13,14] gave an overview about a variety of energy and electricity system models with their classification and features. [15] Discussed the current challenges facing energy systems models, where [16,17] interpreted the crucial considerations of open-source modelling.

Expansion models optimize generation and grid capacities to advise decision-making on investments, given indications or assumptions about future electricity demand, fuel prices, technology investment cost and performance, along with governmental policy and regulation [18].

There are numerous expansion models of the electricity system focussing on optimization of the whole time-horizon with a perfect foresight. TIMES [19], a dynamic intersectoral optimization model is employed by multiple users on different scales and scenarios (nationally and internationally) [20]. LORELEl [21] optimizes the expansion of different renewable energies under given support systems in Europe in a dynamic interregional investment model. ENTIGRIS [22] supports grid development planning in Europe and North Africa by studying the regional specific potential of renewable and conventional power plants and their long-term portfolios. E2M2 [23] optimizes the European utility's dispatch, power plants investments decisions, and spot market prices for the electricity and heat sectors with a high range of demand flexibility, while Powerflex [24] identifies the optimal operation of power plants by exploring the flexibility of supply and demand in short-term markets covering the German and Dutch systems. ELIAS [25], a power plant expansion and investment cost model for the German electricity sector that determines the most cost-effective operation of energy system under ecological conditions and inspects the renewables impact on the power plant fleet, and the cross-sectoral energy system model REMod [26] investigates different demand sectors in Germany to identify the future market shares of renewables and optimizes their operation modes and interactions amongst all sectors to determine the cost-optimal transformation. SCOPE [27] maps all demand sectors without regional resolution in Germany to identify the future electrical demand in a cross-sectoral cost-optimized energy system and determine the participation of heat and transport sectors in achieving the climate target. In addition, REMix [28] identifies the least-cost combination of renewables to satisfy the energy supply system in Germany, allowing energy trading across Europe and neighbouring countries.

In contrast to the perfect foresight expansion models, myopic expansion models optimize shorter time horizons with a sequential decision-making process. Therefore, they are able to account for uncertainties in the energy system and offer more accuracy, yet require more computational effort and complexity. While current renewable generation technologies are already well integrated in the energy systems, many studies suggested they will face sharp drops in their costs in the next decade. As pointed out in [29], the cost drop can follow different behaviour in terms of when it is happening. Myopic expansion offers a realistic and precise modelling of the energy system, and avoids the energy system uncertainties, allowing for a successive decision-making process [30].

PyPSA-Eur-Sec [31] is an inter-sectoral model of the electricity, heat and transport sectors in Europe with a myopic planning horizon of 5 years. My-UK Times [32] and ESO-XEL [33] models address the UK energy sector with different myopic foresight and overlapping time steps to examine their effect on the expansion of the energy sector. A myopic approach is applied to LUSYM in [34], where the investments optimization is compared between a perfect (30 years) and short run (10 years) foresight on the Belgian electricity system. A myopic approach with 5 years planning horizon is introduced to the PERSEUS-NET model in [35] for the German electricity system until 2030. DISTRICT [36] focuses on the economic analysis of the opportunities in a German district, including sector-coupling and flexibility technologies with a limited foresight horizon (5 years).

While the energy system models and the myopic planning approaches already exist in literature, there is currently no open-source myopic model that adequately maps and focus on the German electricity sector in detail, with a high spatiotemporal resolution, nor offer the ability to take into consideration the regional expansion limitations and differences. To overcome this gap, this research introduces a new version of PyPSA-Eur model [37], with a focus on the German electricity system with a myopic planning approach: MyPyPSA-Ger, a cross-regional electricity system brownfield model of Germany, and a detailed representation of the transmission network in Germany, with high spatial (up to 317 nodes) and temporal resolutions (up to 8760 h a year), an updated temporal characterization of the network by means of generation, demand profiles, and dynamic cost assumptions, with

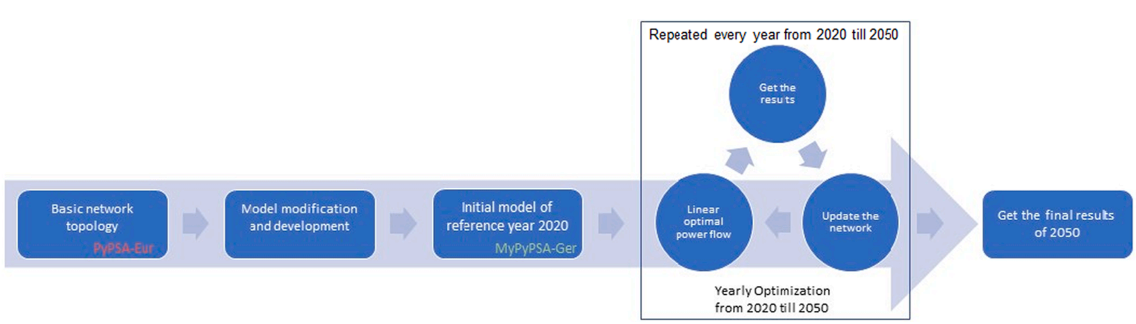

Fig. 1. Model development procedure.

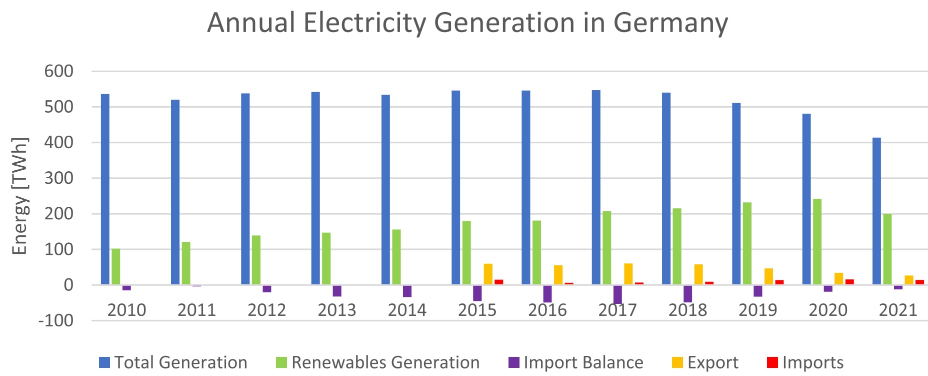

Fig. 2. Annual electricity generation and imports in Germany [39] (For 2021: until mid of November).

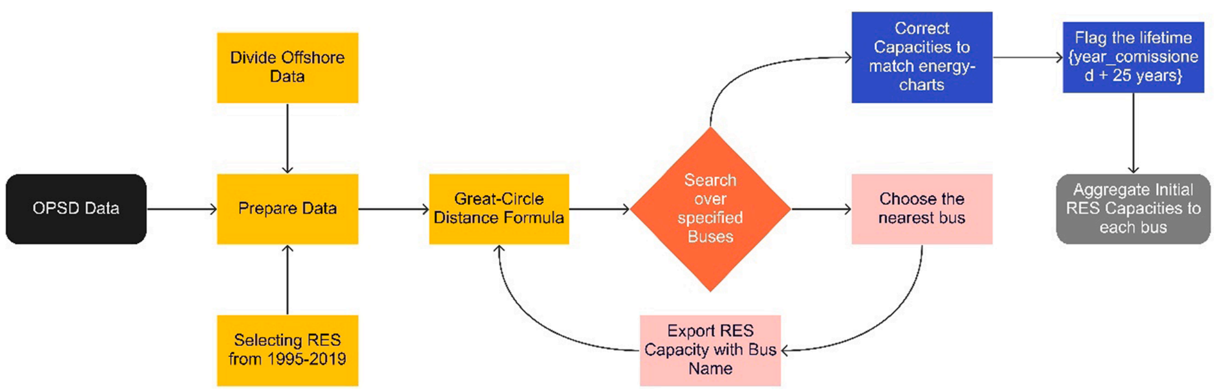

Fig. 3. Renewable energy power plants mapping.

regional investments rates and social constraints.

The novelty of this open-source model, is that it considers regional differences in Germany by applying regional and yearly investments limitations, and offers the ability to construct an optimal myopic roadmap of the German energy transition path to 2050. Moreover, the model has around two million conventional and renewable power plants, allocated over a clustered electrical network with an aggregated capacity profile. The ever-changing technologies investment costs and electricity demand are taken into account with the ability to have a dynamic learning curves over the planning horizon.

As the market design is not fully suited for renewable integration, this research seeks to identify the impact of the CO_2 tax on the energy transition and the employment of renewables. As such, this research offers new lookouts on the energy transition and the diverse German electricity system.

2. Methodology

This chapter describes the methods used to develop MyPyPSA-Ger model. The whole modelling framework and subsectors are shown in Fig. 1. The idea of the model development, is to create a basic model that sufficiently represents the German energy system; spatially and temporally, then modify it to the actual state of the energy system of beginning of 2020, to be employed as the reference year to start the optimization process. Afterwards, a myopic optimization method is applied till the year 2050, where the optimization results of each year will be the input of the year after. The network, its elements, costs, limits, electrical demand, and constraints are updated on a yearly basis.

The scope of this study will not consider the interconnection between Germany and its neighbour countries. Recent trends of Germany's imports and exports [38,39] (refer to Fig. 2) show, that Germany is exporting to neighbour countries, whereas most imports are transmitted to other European countries [40]. This comes in line with [41], which concluded that the level of reliance on interconnection tend to decrease with the rapid increase in renewables. In addition, two scenarios in [42] were discussed, where an optimized self-sufficient German energy system scenario is currently being pursued in Germany, and seems more likely to happen. Not to mention, in all internal scenarios of the ENTSO-E report [43], Germany was, in terms of import/export, either balanced or an exporter in Europe. In other words, having no interconnection in the model might have an impact on the level of RES curtailment, but a smaller impact on the load shedding.

3. Initial network topology

Python for Power System Analysis (PyPSA) is an open-source modelling framework [44], that offers the ability to simulate and optimize electrical networks. The network can model conventional power plants, variable renewable energy systems, electric demand, storage units, coupled with mixed AC and DC networks. The basic network is created through PyPSA-Eur; an open-source model of the European power systems on the transmission level [37], depending on PyPSA. A cut-out for Germany can be made possible by means of the model's configuration, which creates a well-clustered network of the German energy system. The network includes the aggregated and simplified 380 kV transmission capacity with the HVDC links. The electricity demand of the network is distributed over the buses based on linear regression analysis of gross domestic product and population [37].

4. Basic model modification

The Network setup from PyPSA-Eur is a starting point for the model developed in this paper. As the model is developed through a brownfield approach, the cut-out for Germany's energy system is adapted to

Table 1
Technologies capacities in GW from different reports in 2019.

Technology	Energy-charts [38]	SMARD [50]	Agora [51]	ENTSOE [52]	Bundesnetz-agentur [53]	PyPSA-Eur[a]
Solar	49.1	48.2	49.2	45.4	51.4	47.9
Onshore wind	53.2	53.2	53.4	52.9	53.7	53
Offshore wind	7.5	7.5	7.7	6.4	7.7	7.1
Run-of-river	3.9	9.4	4.8	4.0	3.5	2.9
Hard coal	22.7	22.5	23.7	25.3	23.7	21.9
Brown coal	20.9	21.1	21.1	21.2	20.2	20.8
Gas	30.1	31.7	30.7	31.7	26.7	23.9
Biomass	8.5	7.9	8.3	7.8	8.6	0.8
Oil	4.4	7.5	8.7[b]	4.4	3.9	3.7

[a] Renewables installed capacities are from OPSD data
[b] With other conventional generation technologies

Table 2
Average capacity factor values of solar and onshore wind power plants in Germany.

Technology	UMWELTBUNDESAMT [58]	BMWI [59]	BDEW [60]	ISE [61]	Wuppertal [62]	Agora [63]	EWI Cologne [64]	Renewables ninja [65,66]	PyPSA-Eur[a]
Solar	10.2%	10.9%	11.2%	10.6 – 14.6%	11.4%	10.4%	11.4%	13.14%	9.2%
Onshore wind	34.2%	20.3%	21.9%	20.5% – 36.5%	28.5%	26%	19.9%	23.79%	19.6%

[a] For a 16-node network.

Table 3
Lines lengths comparison.

Voltage Level (kV)	Line Lengths (km)*	
	MYPYPSA-GER	ENTSOE-E [68]
AC – 400	–	21709**
AC – 380	23,754	–
AC – 220	–	13,069
DC	1379	1307***

* for 16 node network
** 2020 value forecasted from [68] data
*** 2018 value

represent the beginning of the year 2020 as a reference year, hence MyPyPSA-Ger. In the following only the changes to PyPSA-Eur [45] are displayed, to achieve the myopic model MyPyPSA-Ger for Germany.

4.1. RES capacities mapping

Renewable power plants and capacities are mapped to the network as summarized in Fig. 3.

The Open Power System Data (OPSD) data is used to map the renewable energy capacities, as they offer around 1.9 million power plant entries of all renewable energy power plants, with spatial information, rated capacity and commissioning dates for each entry [46]. OPSD contains data that are supported by the German Renewable Energy Law (EEG), which includes small and large scale, private- and state-owned power plants. The OPSD gives information about solar, onshore and offshore wind technologies as well as other technologies such as hydro, bioenergy and geothermal power plants. Offshore wind data have no information about the transmission technology (AC or DC). Moreover, the offshore wind plants which have spatial information (known plants) accounted for only around 1.66 GW out of 7 GW total available capacity in the dataset, meaning that around 5.4 GW of unknown plants. Therefore, an algorithm was developed for an approximate mapping of offshore wind data, as shown below.

Algorithm 1: Mapping offshore wind data

Step 1	:	Average latitude value of known plants → latitude info for unknown plants
Step 2	:	List of values of known longitudes of known plants → randomly assigning longitude position for unknown plants (N*umpy.random_choice* [47])
Step 3	:	For idx in (offshore_data)
	:	If idx == odd number
	:	Offshore_data → DC technology
	:	If idx == even number
	:	Offshore_data → AC technology
Step 4	:	Return Offshore_data
Step 5	:	End procedure

In step 1, the latitude minimum and maximum values of all the known plants are 53.9 and 54.8, respectively. Assigning the average latitude value of them to the unknown plants can be a valid assumption, given the location properties of Germany, where offshore wind plants are planned in the North and Baltic seas [48]. Longitude missing values are randomly assigned from the longitude values of known plants. Moreover, the selection of renewable power plants assumes a lifetime of 25 years for all renewable technologies, meaning that only power plants that were commissioned after 1995 will be considered.

The prepared datasets are analysed using the haversine approach to calculate the Great-Circle distance, to allocate each plant to the nearest node in the network, assuming a direct, uninterrupted and straight connection between the node and the plant [49]. From the original network topology, not all busses contain all renewable technologies to respect the country's geographical properties. From this fact, the renewables plants will be mapped only to a selected group of buses, that contain a certain type of technology. A sample of the final dataset is shown in Table 11 in the Appendix B.

Algorithm 2: Mapping renewables data		
Step 1	:	Convert longitude and latitude to angles, in buses and renewables dataset
Step 2	:	Obtain a list of selected buses that have a certain power plants technology
Step 3	:	Haversine formula
	:	$Bus_{nearest} = \min[arccos(sin\beta_b * sin\varnothing_p + cos\beta_b * cos\varnothing_p * cos(\Phi_b - \Theta_p))*6371] \forall b in network nodes, p in OPSD dataset$ Where: Θ: power plant longitude ∅: power plant latitude Φ: bus longitude β: bus latitude
Step 4	:	End procedure

4.2. Correcting initial capacities

The initial capacities from the year 2019 of installed conventional power plants and the mapped renewable power plants vary from the actual capacities in Germany reported from several studies, as shown in Table 1. The difference between sources is due to multiple reasons, such as the data collection approaches and degree of transparency.

Comparing the values of the different sources, hence the initial capacities of biomass, coal, and gas will be corrected promptly, with the modified new capacities shown in Table 4. OPSD datasets of power plants include biomass as one of the technologies, in which spatial information is available for each plant [46]. The same procedure as explained in Fig. 3 will be implemented, each with a lifetime assumption based on Table 5.

Coal-fired power plants data are available in OPSD [46]. Only power plants that were not shutdown will be included, with a lifetime of 50 years [54]. An extra lifetime of 20 years as well is assumed for power plants that were retrofitted, after updating their commissioning year [55]. The same procedure as explained in Fig. 3 will be implemented.

For CCGT and OCGT plants, the OPSD conventional power plants dataset doesn't offer a detailed description of the efficiencies of each gas-fired power plant to differentiate OCGT from CCGT [56]. Therefore, the available power from CCGT and OCGT is increased by 126% to increase the initially installed power while maintaining the detailed specification of each generation technology.

Table 4
Installed generation capacities comparison in GW.

Technology	SMARD [50]	MyPyPSA-Ger
Solar	48.2	47.9
Onshore wind	53.18	53
Offshore wind	7.5	7.07*
Run-of-river	9.4**	2.907
Hard coal	22.458	20.03
Brown coal	21.067	20.83
Gas	31.7	30.07
Biomass	7.98	7.950
Oil	7.5***	3.696

* of which 3.534 GW AC connection and 3.536 GW DeC connection
** Including pump storage
*** With other unspecified conventional technologies

Table 5
Lifetime assumptions in years.

Technology	ISE2020 [4]	IEA2020 [72]	LCOE2018 [74]	MyPyPSA-Ger
Solar	26	25	25	25
Wind (Onshore)	24	25	25	25
Wind (Offshore DC & AC)	20	25	25	25
CCGT	40	30	30	30
OCGT	40	30	30	30
Coal/Lignite/Oil	45	40	40	40
Biomass	–	–	30	30 [75]
Run-of-river (ror)	–	80	–	80

4.3. Adapting electrical demand

The electrical demand in the basic model is distributed with the same demand profile over the different clusters. However, the yearly demand in the model is 463 TWh, while the estimated load of 2020 is nearly 543 TWh [57]. Therefore, the overall demand shall be increased to 117% to reach the aforementioned value. The lack of detailed and disaggregated electrical demand data will, however, affect the regional characteristic and behaviour of the load profile and its peak values.

4.4. Adapting generation profiles

The renewable energy generation profiles generated in the basic model suffer from nodes aggregation in the original network clustering topology as shown in Table 2. The average capacity factor (CF) and full load hours (FLH) values are below expected values for Germany.

Moreover, the maximum capacity factor in the original model for solar and onshore wind is 9.8% and 28%, respectively[4]. This means that even very good locations in terms of weather, wind speed, and irradiation are below the expected values in Germany, due to the applied method of nodes aggregation [37]. Nevertheless, the maximum CF values have, up to a certain disaggregation level, a direct correlation based on the number of selected clusters and time resolution of the model as shown in Fig. 4.

Therefore, an updated hourly resolution generation profile is used [65,66], as the renewables ninja tool offers the ability to fetch CF profiles for solar and onshore wind powerplant, based on each plant geographical location. This will enhance the deployment of solar and onshore wind in the model and strengthen the model representativity of the German energy system and geographical properties.

The finalized brownfield model, MyPyPSA-Ger, which represents the beginning of the year 2020, will then have a detailed mapping of conventional and renewable power plants, adapted generation and demand

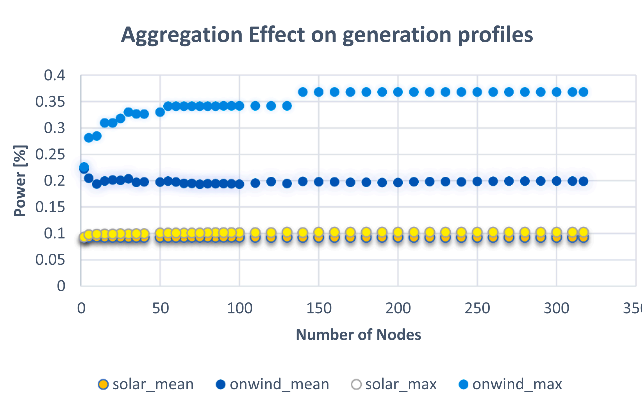

Fig. 4. Correlation of clustered network and CF for solar and onshore wind power plants.

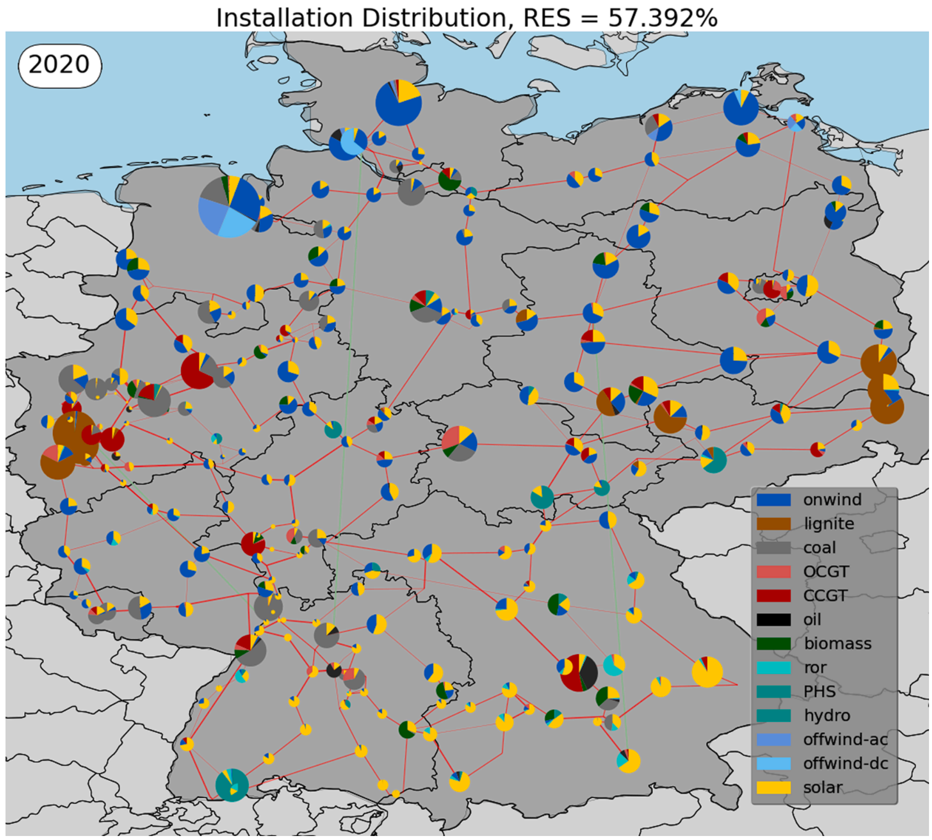

Fig. 5. Basic model of the German energy system for the year 2020

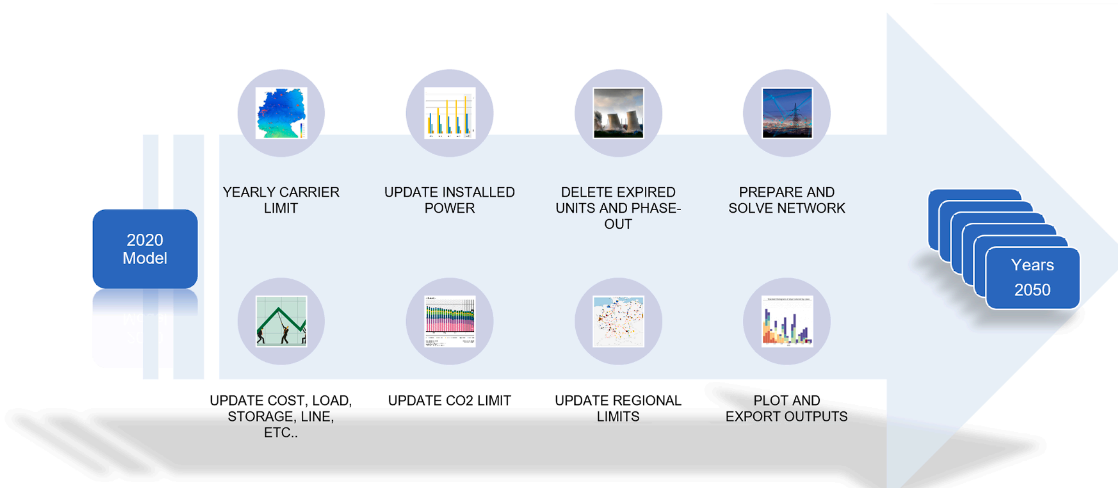

Fig. 6. Myopic process of network optimization.

profiles, corrected initial capacities and costs. The source code for the basic model will be made open-source and available along with the used input data and can be clustered up to 317 nodes for the German transmission network. The model is shown in Fig. 5.

4.5. Data/model validation

After adapting the basic model, the network components and ratings are compared to the validated official values. First, Table 3 compares the total AC and DC line circuit lengths of different voltage levels with the historical grid capacity dataset published from ENTSO-E [67], which covers the AC line capacities up to 2015 and DC links up to 2018. The network is aggregated and simplified to one voltage level (380 kV [37]) to reduce its computational needs and complexity in the optimization process. The ENTSO-E 2020 AC lines lengths value is estimated through an exponential smoothing forecasting algorithm using the published data from 1975 to 2015 to get a better approximation [67].

The initial power plants capacities of MyPyPSA-Ger are shown in Table 4.

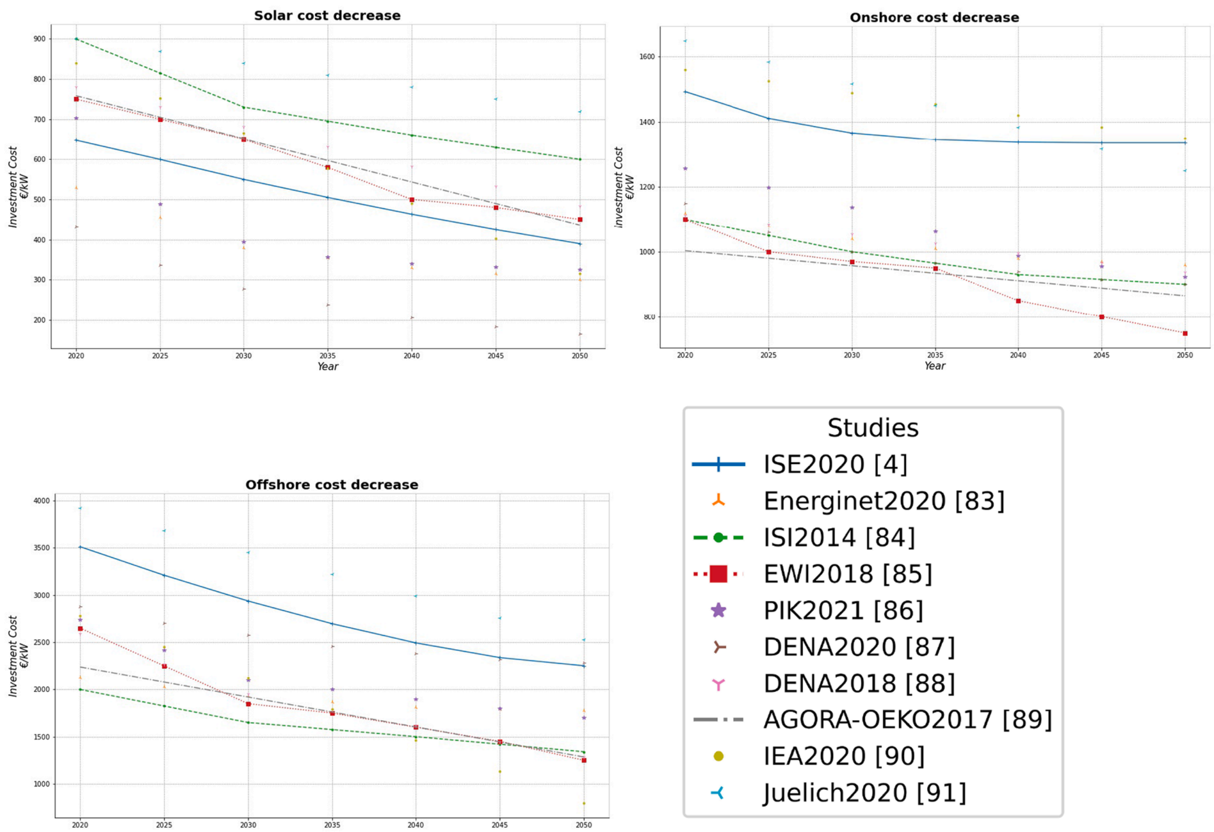

Fig. 7. Cost decrease of renewable technologies over 2020–2050.

5. Myopic approach

The idea behind the myopic approach, is that the optimization output of each year would be the input of the next year. The optimization output is in terms of generation investments, power plants shutdown, electric demand, and network operation constraints. The objective of the optimization is to minimize the total system cost on a yearly basis as shown in Fig. 6.

5.1. Adding elements lifetime

A lifetime is added to each element in the network, either already existing capacities that were commissioned before the 2020 basic year, or the future investments within the study's planning horizon. Network connection components such as AC lines and DC links are assumed to have lifetimes (up to 100 years) longer than this study's scope (30 years) [69]. Moreover, the basic grid infrastructure is assumed to be at least constant for the next 30 years, meaning that the actual high voltage links and lines of 2020 are assumed to be operational until 2050. Storage units capacities are mainly from pumped hydro storage and hydro reservoirs, with a longer lifetime with their capacities being constant during the whole optimization horizon [70–72]. As the focus of this study is the regional differences of renewables investments and the influence of CO_2 tax on the energy transition, initial capacities of storage technologies such as H2 and battery storage are not accounted for, where their current installed capacity in Germany is yet in a smaller and limited range and can be negligible [73]. Table 5 summarizes the lifetime assumptions for the network's components compared to different studies.

5.2. Create fixed components

Some network elements are included in the optimization process to help satisfy the network's constraints, namely generators, lines and links. All the aforementioned components have an option that upon activation enables their nominal power expansion under their technical and regional constraints and geographical potentials. However, since the original model solves the optimization problem with perfect foresight, it is essential to store the components previous nominal ratings while enabling the expandable option, simultaneously. To overcome this issue, the same component will be appended to the network at the same location of each expandable component, with the prefix "Fixed", a deactivated expansion option and a zero capital cost so it will no longer take part in the total system cost optimization. The goal behind this is to store the investments by the optimizer on a yearly basis, and to treat them as a pre-existing component of the network, with the same weather dependency and generation profile. Moreover, the maximum technical potential of each expandable generation unit will be stored in the fixed part, so that regional potential constraints can be applied to the expansion process. This process is implemented through the following equations.

$$X_{g,n,i=2020} = \sum_{i=2019-É©_g}^{i=2019} X_{g,n,i} \forall allginextendables\# \quad (1)$$

$$M_{tg,n,i=2020} = M_{tg,n,i=2019} - X_{g,n,i=2020}\# \quad (2)$$

$$\varepsilon_{g,n,i=2020} = 0\# \quad (3)$$

$$[\varepsilon_{g,n,t}]^{max} = [x_{g,n,t}]^{max} = á¿¶_{g,n,t} \forall ginrenewables \quad (4)$$

For the lines and links, the actual grid infrastructure is represented by adding the same elements without the expansion option and a capital cost of zero, while the expanded elements are kept with an initial current carrying capacity of zero to be expanded in the following years, upon optimization decision.

$$\square_{\mathcal{L},Ü,i=2020} = \square_{\mathcal{L},Ü,i=2019} + \nu_{\mathcal{L},Ü,i=2019} \quad (5)$$

Table 6
Model cost assumptions [4,83–91]

Technology	Investment Cost[a] [€/kW]							O&M[% of CAPEX]	O&M[b] [€/MWh]
	2020	2025	2030	2035	2040	2045	2050		
Solar	648	600	550	505	463	425	390	2	0.1[c]
Onshore wind	1257	1197	1137	1062	987	955	923	3	1.5
Offshore wind[d]	2736	2419	2102	2000	1900	1800	1700	3	3
CCGT	800	800	800	800	800	800	800	3.75	4.4
OCGT	400	400	400	400	400	400	400	2.5	4.5
Coal	–	–	–	–	–	–	–	1.6	2.9
Lignite	–	–	–	–	–	–	–	1.6	2.9
Biomass	2350	–	–	–	–	–	–	3.6	2.1
Run-of-river (ror)	2500	–	–	–	–	–	–	2	0.1[d]

[a] Only for extendable technologies.
[b] Variable and fixed operation costs are assumed to be constant over the years
[c] To compensate and reduce RES curtailment.
[d] Connection cost accounts for 18% of the total investment cost [81].

Table 7
Fuel cost assumptions [4,92–94].

Technology	Fuel Cost [€/MWh$_{thermal}$]						
	2020	2025	2030	2035	2040	2045	2050
Gas	31.5	35.7	39.8	42.1	44.4	46.6	48.9
Biomass	26.38	27.12	27.86	29.13	30.4	31.67	32.94
Coal	8.73	9.4	10.1	10.4	10.7	11.1	11.4
Lignite	3.2	3.4	3.6	3.7	3.8	3.9	4
Oil	46.4	59.3	72.3	76.5	80.7	84.9	89

$$\nu_{\mathscr{L},\ddot{\mathrm{U}},i=2020} = 0\# \tag{6}$$

The initial newly added generation and newly added branch capacity are set to zero only in the initial model before the start of the myopic optimization.

5.3. Update load

Many studies outlined the electricity demand in Germany will face huge changes by the year 2050 based on many scenarios [4,76–78]. By 2050, the electricity share in the total final industrial consumption is expected to double, from 21% in 2020 be around 46% in 2050, as well as a transport sector completely dominant by electric appliances [79]. Electricity demand for an electrified transport sector could amount for an additional 900 TWh by 2050 [80]. Moreover, the electrification of final consumption sector (heat pumps) is expected to increase the electricity demand by 75 TWh by 2050 [81]. At least 60% electrification degree is expected in the heat demand for household and industrial sectors as well as the transport sector, resulting in at least doubling the electricity demand by 2050 [4]. The transition of electricity sector is the most vital step towards achieving climate neutrality. Therefore, the electric load in MyPyPSA-Ger can be changed and updated annually either on a linear or dynamic learning rate. This step is crucial to represent the future electricity demand, and can be changed depending on the implemented scenario, as explained in the equation below.

$$\sum \partial_i = \sum \partial_{i-1} {}^* fd_i \# \tag{7}$$

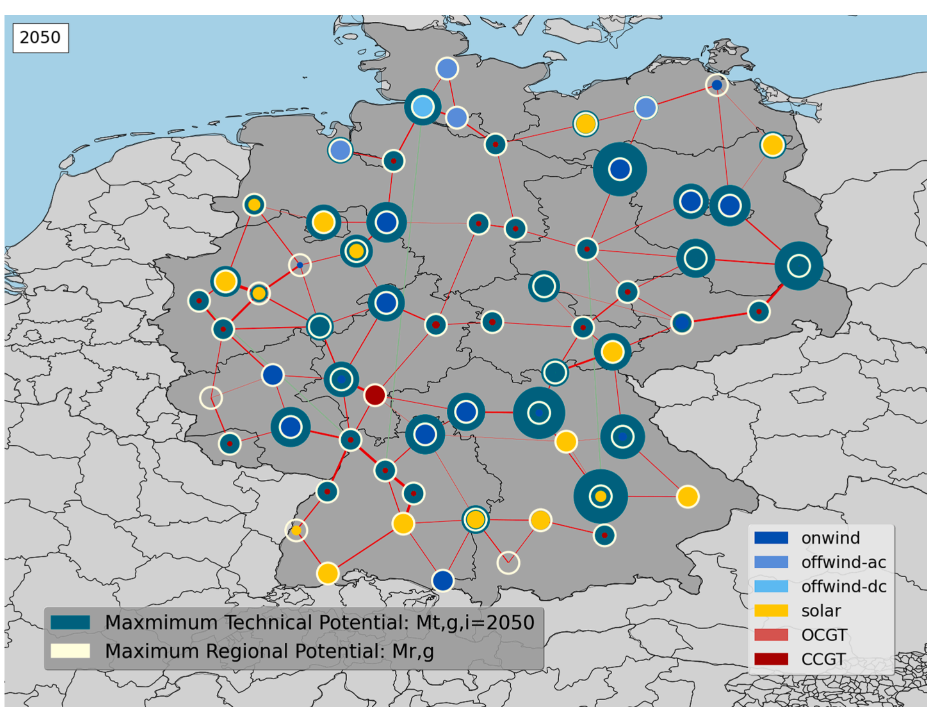

Fig. 8. Exemplarily regional technology potential in the year 2050

5.4. Adapt initial cost and update cost

Many studies reported different values for investment, fixed, and variable operation and maintenance costs, as well as fuel costs. The cost assumptions of the original PyPSA-Eur model refer to a cost of a certain year in the planning horizon. However, this has to be adapted in the initial model so that the output would reflect the 2020 reference year case. Moreover, as the cost of different technologies will vary over the course of the next 30 years, it is important to match this change with a proper description within the model. The capital and marginal costs of all extendable components will be multiplied by an annual cost change factor. The cost factor is determined by a saturation function from several studies, where the cost assumption of different years is available with a higher horizon (5 or 10 years). The saturation function estimates a yearly growth/shrink factor and then calculates the associated cost of each element yearly. For conventional technologies, the marginal cost will change with time, as the capital cost is of no interest for the scope of this study, excluding CCGT and OCGT. Also, the marginal cost of all conventional technologies will take into account the changing fuel cost over the years. The cost assumptions are shown in Fig. 7 and summarized in Table 6 and Table 7.

The cost update over the years functions as follows.

$$\kappa_{g,i} = \kappa_{g,i-1} {}^{*} fc_{g,i} \# \tag{8}$$

$$o_{g,i} = o_{g,i-1} {}^{*} fc_{g,i} \forall g in renewables \# \tag{9}$$

$$o_{g,i} = VOM_{g,i-1} {}^{*} fc_{g,i} + \frac{\text{Æ-}_{g,i}}{\eta_g} \forall g in conventional \# \tag{10}$$

5.5. Set yearly and regional investment limits

In Germany, the maximum potential for the expansion of renewable technologies is based on the technical, environmental, social and political constraints. These values are 441 GW, 350 GW, and 87 GW for onshore wind, solar and offshore wind, respectively [37]. In reality, not only good locations are used in energy system investments due to land-use, and most importantly, social acceptance. However, as MyPyPSA-Ger optimizes the energy transition with a myopic approach, this generic approach has to be changed promptly. Therefore, two constraints are introduced to the model, a yearly and regional maximum expansion limit. The yearly potential is responsible to restrict the maximum allowed expansion rates of each technology at a certain year, where the regional potential is introduced to each technology at each node of the network. The regional potential limits the expansion rates in a certain node, where the yearly potential limits the model's preference and utilization of only one technology. These yearly and regional expansion potentials, for each technology at each node, are updated on a yearly basis. Moreover, the yearly and regional potentials are not only introduced to renewables, but also extendable generation technologies such as CCGT and OCGT.

The idea behind introducing the yearly and regional limits is to ensure regional realistic installation rates, which might in the end distribute the technologies investments over the country. This can be considered as a starting point to reflect social acceptance aspects in the energy system modelling. Moreover, the regional potential is assigned to all technologies in all buses, only if the maximum potential for that certain technology at a certain bus is greater than the regional potential value. Otherwise, the maximum installation potential, in this case, would be the limiting factor. More to that, the value of the removed capacities from a certain technology at a certain bus is added to the maximum technical potential, under the assumption that the technical potential at any location will not change over time, rather based on the location itself. This means that the maximum technical potential differs from one year to another. The regional and yearly potential allocation is implemented based on the following equations:

$$\mathrm{M}_{tg,n,i} = \mathrm{M}_{tg,n,i-1} + \varepsilon_{g,n,i-\text{É©}_g} - \varepsilon_{g,n,i-1} \# \tag{11}$$

$$0 \leq \varepsilon_{g,n,i} \leq \mathrm{M}_{rg,n} \tag{12}$$

$$0 \leq \varepsilon_{g,n,i} \leq \mathrm{M}_{tg,n,i} \tag{13}$$

$$0 \leq \sum_{n} \varepsilon_{g,n,i} \leq \mathrm{M}_{y_{g,i}} \tag{14}$$

Fig. 8 explains this approach, which is automatically produced for each year on every optimization run. It shows at each node which technology was hugely invested in at a certain year, along with its maximum installable potential of that same technology. For instance, wind technology has a higher technical potential and a better capacity profile in the north of Germany. This however does not mean that all this potential will be utilized in a single year to cover the demand. Moreover, it shows how the model works in terms of which technologies to invest in, and where to invest, and how the regional and yearly potential limits the investment rates. Not to mention that for CCGT and OCGT, there will be no maximum technical potential, meaning that it will be limited by only regional and yearly potential. Moreover, it can happen that in some nodes, the available technical potential is less than the regional potential, which in this case, the newly added generation capacity will be limited by the lower value, hence the maximum technical potential left in that node. As a summary, the newly added installations are always limited by either the maximum technical potential left in that node, or the regional potential assigned to the whole network, whichever is lower in each node.

The recent trends of renewables expansion in Germany give an idea about the yearly and regional technologies potential values. The OPSD dataset [46] is used to allocate the amounts of installed renewables yearly, alongside the network nodes geographical information, to determine the regional installations based on the nodes distribution in the model. However, these values were adapted to satisfy the model based on several model runs. Not to mention, the regional potential over the planning horizon has to be changed in accordance to the implemented scenario. This means that the current expansion trends, country- and regionwide, will most probably be inadequate to achieve the energy transition goals, and have to be increased accordingly. Moreover, having wide-open yearly and regional potential values, will vary the model results from a conservative potential value. It is also worth mentioning, that the higher capacity factor and technical potential in better locations will play, indirectly, a major role in deciding when, where, and which technology to invest in.

5.6. Update fixed branches

The fixed generation components will be updated annually with the new optimal rated power. Also, a lifetime value is added for each technology at each bus annually with the optimized value. Moreover, the removal of outdated power plants is executed promptly at the beginning of each optimization year. For the grid infrastructure, the same approach is implemented as in the generation expansion, where the fixed elements are updated with the new grid infrastructure rated power and number of parallel lines. Also, the grid infrastructure will not be restrained by any expansion limits. The update approach is implemented based on the following equations.

$$\mathrm{X}_{g,n,i} = \mathrm{X}_{g,n,i-1} + \varepsilon_{g,n,i} - \varepsilon_{g,n,i-\text{É©}_g} \# \tag{15}$$

$$\boxed{?}_{\mathcal{L},\text{Ü},i} = \boxed{?}_{\mathcal{L},\text{Ü},i-1} + \nu_{\mathcal{L},\text{Ü},i} \tag{16}$$

5.7. Update network constraints

The network constraints are updated annually to construct a road map for the German energy system, these are CO_2 limits, line loading

Table 8
Scenarios settings.

Scenario name	Annual electrical demand increase in %	CO_2 reduction goals in %/a[a]	CO_2 allowance cost in €/tCO_2	regional potential in GW/node	Yearly potential in GW/a	Coal Phase year
Reference	1%	no decrease	25 Fixed	3	30 GW for RES10 GW for CCGT & OCGT	only whenoutdated
2050 N	1%	55% by 2030 70% by 2040 95% by 2050	25 Fixed	3	30 GW for RES 10 GW for CCGT & OCGT	2037
2050N_ CO_2tax	1%	55% by 2030 70% by 2040 95% by 2050	25 in 2020 100 in 2030 150 in 2050	3	30 GW for RES 10 GW for CCGT & OCGT	2037
2050N_ early_CO_2tax	1%	55% by 2030 70% by 2040 95% by 2050	25 in 2020 200 in 2050	3	30 GW for RES 10 GW for CCGT & OCGT	2037
2050N_ Rapid_CO_2tax	1%	55% by 2030 70% by 2040 95% by 2050	25 in 2020 200 in 2030 200 in 2050	3	30 GW for RES 10 GW for CCGT & OCGT	2037
2050N_ early_phase	1%	55% by 2030 70% by 2040 95% by 2050	25 Fixed	3	30 GW for RES 10 GW for CCGT & OCGT	2030

[a] With respect to 1990 values.

and line expansion limits, load shedding, and technology investment potentials. The objective function of the model is constructed in the basic model [37]. However, the changes implemented in MyPyPSA-Ger model are presented below, which basically includes adding the myopic optimization to the objective function, and how the network elements change annually. The objective function of the model is minimising the annual system cost as follows:

$$\min_{\substack{\mathcal{E}_{g,n,i},\varepsilon_{g,n,t,i}\\ \chi_{g,n,t,i},B_{\mathcal{L},\ddot{U},i}\\ H_{s,n,t,i}}} \sum \left(\begin{array}{c} \kappa_{g,i}\cdot \mathcal{E}_{g,n,i} + o_g \cdot \varepsilon_{g,n,t,i} + o_g \cdot \chi_{g,n,t,i} + \kappa_{\mathcal{L},\ddot{U}} \cdot \nu_{\mathcal{L},\ddot{U},i} \\ + o_s \cdot \left[H_{s,n,t,i} \right]^{+} \end{array} \right) \tag{17}$$

It consists of 1) the newly added generation capacity at a certain year for each technology at each node and their annualized capital cost per capacity with its decrease factor, 2) the dispatch of newly added generation capacity at a certain year and time for each technology at each node and their marginal cost per unit of generation with its decrease factor, 3) the dispatch of already existing added generation capacity at a certain year and time for each technology at each node and their marginal cost per unit of generation with its decrease factor, 4) the newly added branch capacity of a certain branch of a transmission technology (AC or DC) at a certain year along with their annualized capital cost. On top of that, 5) the positive dispatch of storage technologies with their associated marginal cost is added to the total system cost. The optimization is implemented on a yearly basis with varying weather and demand conditions, with the goal of reducing the overall system cost on an annual basis.

The maximum dispatch of generation units, both existing and newly added units, is constrained by either the weather dependent availability in per unit at a certain time and node, or the emissions limit in million tonnes. The weather dependent availability is only valid for renewable generation technologies, where the emissions limit is only for conventional power plants, along with their associated thermal efficiency and emissions factor for each technology.

$$0 \le \varepsilon_{g,n,t} \le \text{á¿¶}_{g,n,t} \forall g in renewables \tag{18}$$

$$0 \le \chi_{g,n,t} \le \tilde{\omega}_{g,n,t} \quad \forall \text{ g in renewables} \tag{19}$$

$$0 \le \sum ɟ_g \cdot \frac{\chi_{g,n,t}}{\eta_g} + \sum ɟ_g \cdot \frac{\varepsilon_{g,n,t}}{\eta_g} \le e_i \quad \forall \text{ g in conventioals} \tag{20}$$

The electricity demand in the model is inelastic, meaning that it has to be met at all times by a sufficient supply from the dispatch of all generation and storage units. More to that, load shedding option is activated from the original PyPSA-Eur as a generation unit with high marginal cost [37], so that in network congestion situations the optimizer has a choice to cover the load at a cost of 100 €/kWh [82].

$$\partial_{i,t} = \sum \varepsilon_{i,g,t} + \sum \chi_{i,g,t} + \sum H_{s,t,i} + \sum \Gamma_{i,t} \tag{21}$$

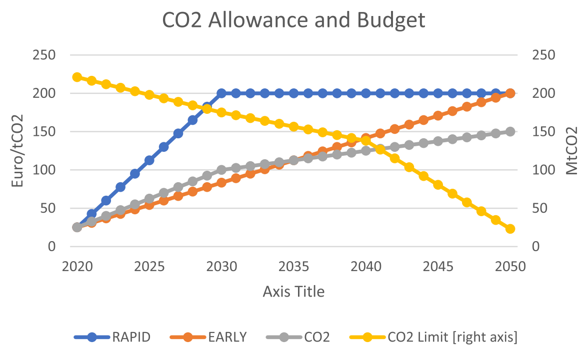

Fig. 9. CO_2 allowance cost for different scenarios along with the budget.

The initial state of charge for the storage technologies is assumed to be empty at the beginning of the optimization. Also, for each year, the final state of charge for any year is the initial state of charge of the year after.

$$C_{s,n,t=0,i=2020} = 0\# \tag{22}$$

$$C_{s,n,t=1,i} = C_{s,n,t=8760,i-1}\# \tag{23}$$

6. Scenarios development

This model is investigated throughout a scenario-based analysis by comparing the results of each scenario, with the aim to give new outlooks for the energy transition. The diversity of the studied scenarios gives an insight into how the future energy sector may differ in the upcoming years. Furthermore, it provides possible pathways to achieve the established government climate goals of Germany.

First, the model inputs and common assumptions are presented, followed by a description of six scenarios. The cost development of different renewable technologies and fuel costs highly affect how the optimization behaves. Therefore, for the sake of analysing the model outcomes in 2050 and the roadmap to it, all cost data will be uniform for all scenarios. More to that, the cost assumptions will follow the modest studies in their cost development for all renewable technologies, as shown in the table below. Biomass and run-of-river technologies are assumed to be constantly present in the energy system with their current nominal powers and without any expansion potential. The model will have the option to invest in retrofitting these plants with the 2020 investment costs. The grid reinforcement costs will remain as in the original model as they are assumed to not expect to face a huge cost development in the future [37,83]. Also, a discount rate of 7% is assumed for the levelized cost of electricity (LCOE) calculations over the lifetime of all technologies [72].

The fuel costs highly affect the choice of the base-load generation technologies, as all generation technologies with fuel costs can operate with a 100% capacity at any time. However, many studies have mentioned multiple reports about the fuel costs, Table 7 presents the fuel assumptions, which are uniform for all scenarios.

By means of scenarios, six different scenarios will be presented in this study. The emission reduction goals published by the federal government in Germany will be analysed [2]. Different scenario settings are shown in Table 8, with the electricity demand values by 2050, CO_2 reduction goals, CO_2 allowance cost and coal phase out dates. A reference scenario is presented with no CO_2 reduction goals, and no phase-out date for coal in order to lay a ground for comparison with other scenarios.

Currently, the heat demand is twice as large as the electricity demand. However, to achieve the emissions reduction targets, the heat, industry, and transport sectors must be electrified and their utilization of electricity has to be increased [77]. The future electricity demand will be driven by electrification of heat and industrial sectors, as well as a shift towards electric mobility. Therefore, an annual 1% increase in the demand is set to represent a conservative degree of electrification in other

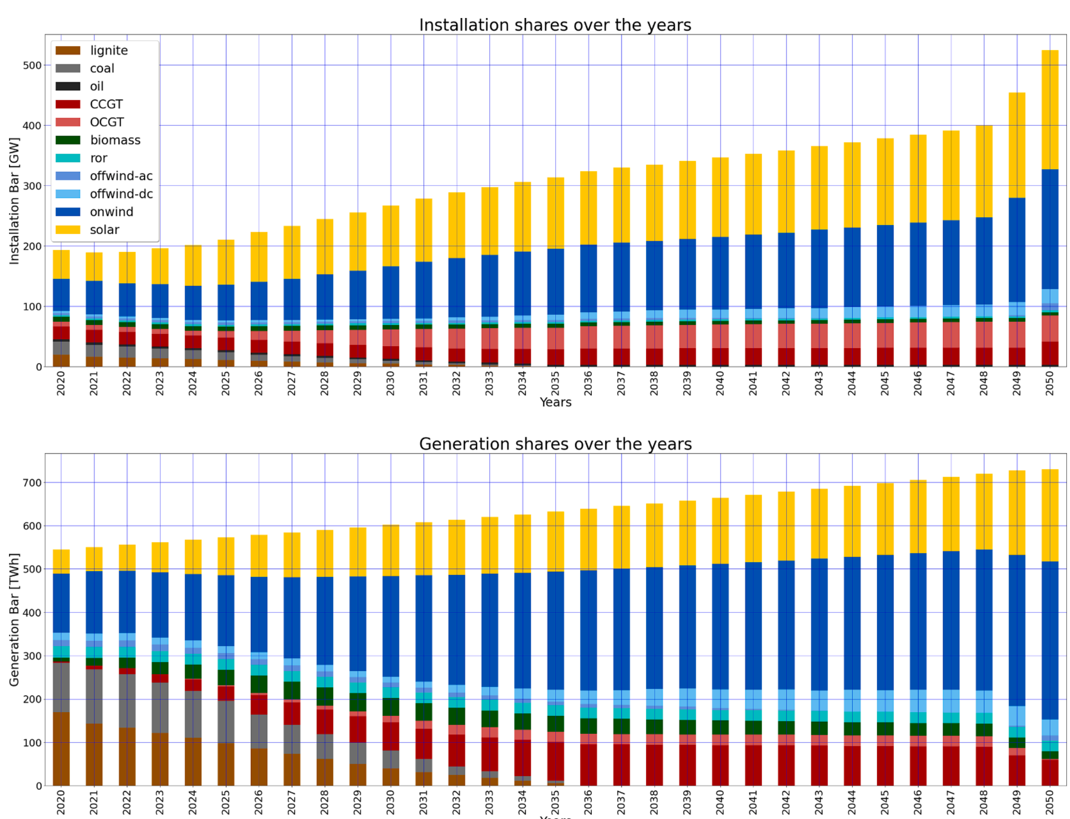

Fig. 10. Installation and Generation shares for 2050 N scenario.

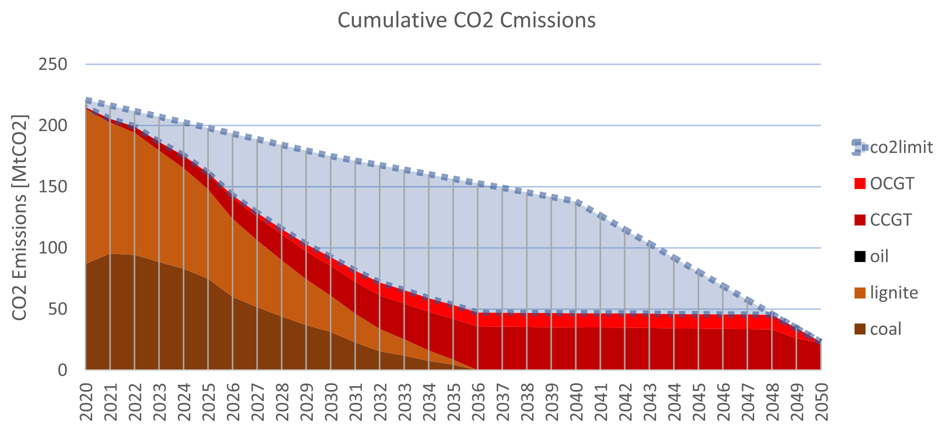

Fig. 11. Cumulative CO_2 emissions for 2050 N scenario.

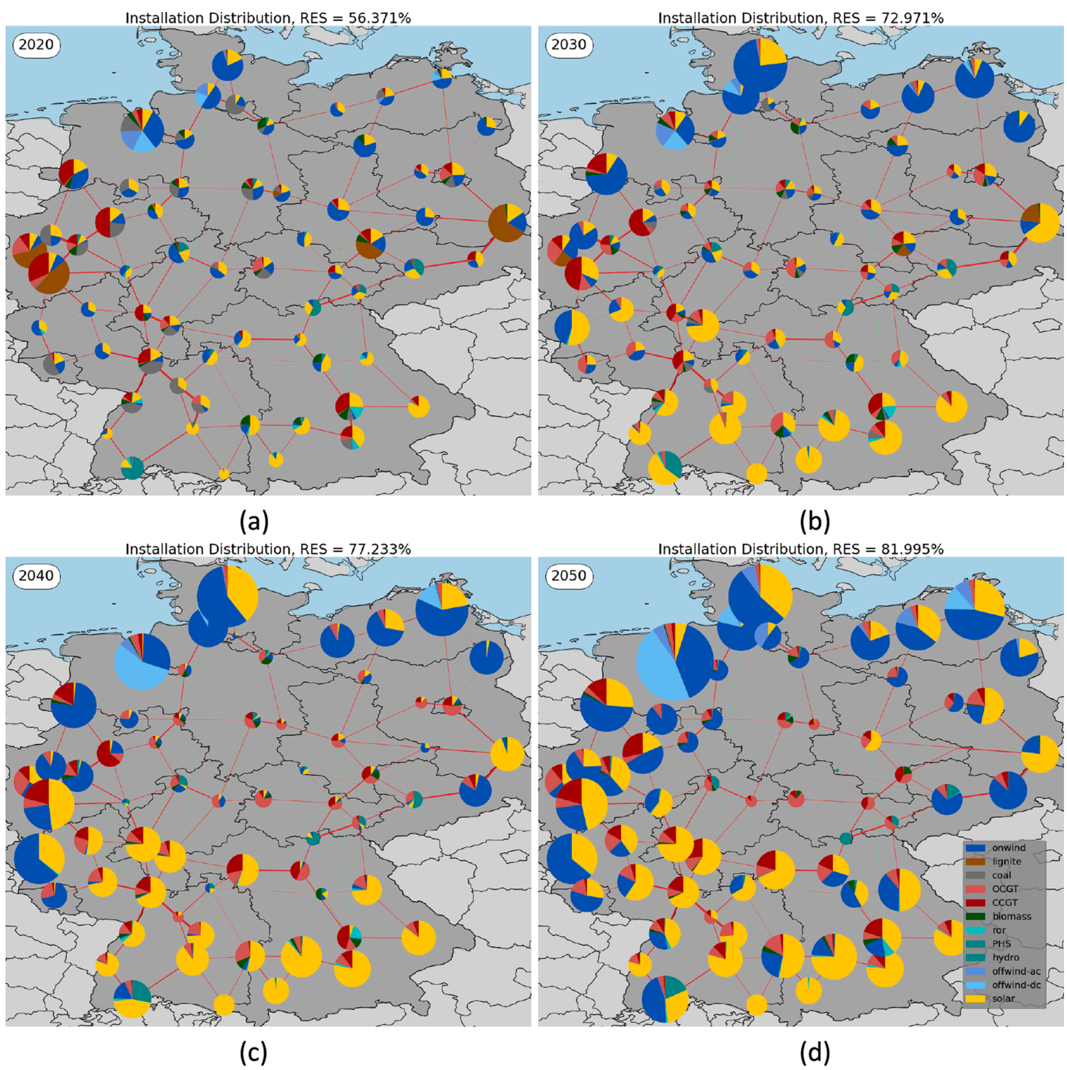

Fig. 12. Regional distribution of installations for 2050 N scenario(Excluding oil technologies)

sectors, either in industrial, transport, or heat sectors.

The (2050 N) scenario will give an outlook over the German energy system goals of reaching 95% CO_2 reduction by 2050. The effect of CO_2 allowance costs is analysed through (2050N_CO_2tax), (2050N_ early_CO_2tax) and (2050N_ rapid_CO_2tax), where in each scenario a different approach of applying the CO_2 tax is presented, as shown in Fig. 9. The (2050N_ early_phase) scenario will investigate the impact of an earlier coal phase-out date. The regional and yearly expansion potentials for extendable generation technologies are fixed. In all scenarios, a linear behaviour is applied on the capital cost decrease, demand growth, and coal-lignite yearly phase-out. The results will be presented on a 64-node network.

Fig. 9 shows the different paths for the CO_2 allowance cost applied in the three CO_2 tax scenarios. Moreover, the calculations to reach the 1.5-degree-target in Germany resulted in having an overall emission budget of 4.2 Gt CO_2 as of 2020 [95], with the electricity sector having a proportion of 32% of the overall CO_2 emissions in the year 2030, and 0% in the year 2050, where to reach the 1.75-degree-target, the budget will be 6.7 Gt CO_2 [95]. Assuming the power system will make 32% out of both budgets, the resulting budgets for the power system will be 2.14 and 1.34 Gt CO_2 for the 1.75 and 1.5-degree-targets, respectively.

The actual emissions from the electricity sector 2019 are 250 Mt CO_2 [96]. To set the CO_2 limits in the model, the 2020 emissions is projected to be 221 Mt CO_2 using linear forecast on the last 5 years values of emissions [96]. By 2030, the government set a target of 60% emissions reduction compared to the 1990 values [2], linearly, reaching 175 Mt CO_2. By 2040, 70% of the emissions need to be reduced [2], reaching 138 Mt CO_2. At 2050, a 95% reduction of the 1990 values is to be reached [2], with a value of 23 Mt CO_2. In order to lay a ground for comparison amongst all scenarios, the summation of the CO_2 governmental targets for the electricity sector over the next 30-year horizon (2020–2050), alone, in this case will be 4472 Mt CO_2. The annual emission limits as projected from the governmental goals are shown on the right axis of Fig. 9.

7. Results and discussion

The reference scenario is presented to compare how will the future energy system look like if no clear policy was enforced. As there is nothing to encourage more renewables investments or limit conventional energy usage, only cost is the main driving factor in this scenario. It can be seen that biomass was completely taken out from the system due to its extremely high marginal cost. The same thing applies to AC offshore wind, as its high capital and marginal cost do not make it a favoured solution compared to other renewables. However, as the demand continues to grow, with the phase out of coal and lignite plants upon their decommissioning dates, renewable energy investments were an attractive source of energy to the system due to their almost zero marginal costs. In this scenario, the question becomes which technology to use on a yearly basis, either investing in more renewables with their high capital cost and very low marginal cost, or using the high marginal cost already-built conventional resources. Therefore, no CCGT was added to the system, as its capital cost was more expensive compared to OCGT. The latter faces a huge investment in the model, but still the least favoured energy source amongst other conventional due to its high marginal cost, meaning that it suffers from low FLH values compared to other technologies. Not to mention, although no CO2 limits were implied to the system, oil was totally neglected as it was the most expensive energy source.

In this scenario, no load shedding occurred as shares of conventional energy remained high. Moreover, unlike other scenarios, gas technologies didn't reach a maximum value of energy mix share as there was no need to heavily invest and compensate for any phase-out, which means it was only invested in after normal plants were decommissioned. It is worth to mention, that renewables still account for 70% of the mix, to confirm that renewables were still the cheapest to invest in, even with the absence of clear policies.

7.1. 2050 N scenario

The reference year 2020 of the model is a starting point for the optimization, where the results of the initial year are estimated through optimization to start the myopic approach. The load in 2020 is 543 TWh, where conventional plants cover around half of that load, mostly from coal and lignite. Renewables represent around 45% of the energy mix, dominated by wind generation. This argument is valid for all scenarios. However, this result does not represent the reality of the current German energy mix, as more renewables are currently employed in the system. The reason behind it is that, in this model, the optimizer is only constrained by the CO2 limits and is not encouraged to use more renewables, even if it is possible. In other words, the decision-making process in the optimizer sees room for development but is not guided to the direction of making this decision.

In terms of installation, renewables account for around 60% of the installed capacity (Fig. 10), with onshore wind and solar dominating with 53 and 48 GW, respectively. Offshore AC and DC wind technologies are present with 3.5 GW each. Coal and lignite are huge parts of the system with roughly 42 GW, along with Gas technologies with approximately 30 GW. Oil was a part of the installed capacity with around 4 GW, however was not used due to its high CO_2 emissions factor and extremely expensive marginal cost. As nuclear plants will be decommissioned by 2022 in Germany, they were not included in the system. Biomass and ror were the last two components of the capacity, with around 8 and 3 GW, respectively.

Over the first 10 years, only few offshore wind plants were invested in (Fig. 10). This is due to the fact that offshore wind was still more expensive than both onshore and solar technologies, 1.5 and 3 times more expensive, respectively. The model invested heavily in solar and onshore wind as they were the cheapest options for investments. Roughly 53 GW were added for solar and 34 GW of onshore wind. OCGT was preferred over CCGT to compensate for the coal and lignite phase-out, with around 20 GW added for OCGT while CCGT remained at an installed capacity of around 21 GW. The reason behind this is that OCGT capital cost was less than half of that of CCGT, even though the OCGT has less efficiency, hence higher CO_2 emissions factor and marginal cost, the model still preferred it over CCGT.

In the energy mix by 2030, coal and lignite were still present in the mix with 41 and 40 TWh, respectively, while oil was completely neglected. CCGT and OCGT were more prominent in the energy mix by 2030, with 65 and 15 TWh, respectively. CCGT was preferred in the energy mix as it has a lower marginal cost compared to OCGT and has the lowest CO_2 cumulative emissions from all other conventional technologies. Biomass was strongly present in the energy mix with 41 TWh and a very high FLH along with 25 TWh of ror. Offshore wind has 24 TWh while solar and onshore dominated the energy mix with 118 and 232 TWh, respectively.

Looking from a regional perspective, most of the solar was built in the southern regions of Germany, while the onshore wind was built in the north (Fig. 12b). This was due to the geographical properties of Germany. By 2030, already 4 nodes out of 64 have reached their maximum potential of solar installed power, all of which were in the state of Baden-Württemberg in the south-west of Germany.

By 2040, coal and lignite completely vanished from the energy mix. Gas technologies were used to cover the base load, with 93 TWh from CCGT and 24 TWh of OCGT. Biomass was still a part of the energy mix with 31 TWh along with 24 TWh of ror. Renewables dominated the energy mix with 77%, mostly from onshore wind and solar, with 289 and 153 TWh, respectively. Offshore wind has around 48 TWh, mostly from DC technology, as they have a better capacity profile compared to AC offshore.

In terms of installed capacities, CCGT and OCGT have slightly increased with 6 and 12 GW, respectively. 6 GW of biomass and 2.7 GW of ror were still part of the system. AC offshore wind was not invested in while DC offshore increased with 11 GW, even though DC has a slightly higher capital cost due to the connection cost, but they have higher capacity factors and higher technical installation potential. For onshore wind and solar roughly 30 GW and 33 GW of extra capacity were added to the system, respectively. Moreover, the massive installation of those technologies between 2010 and 2015 (36 GW for solar and 22 GW for onshore), which was decommissioned within this interval, was compensated along with the additional installed capacities. In other words, during this interval, 69 GW and 55 GW of solar and onshore wind were added to the system, respectively.

In the last 10-year interval, CCGT and OCGT were the only

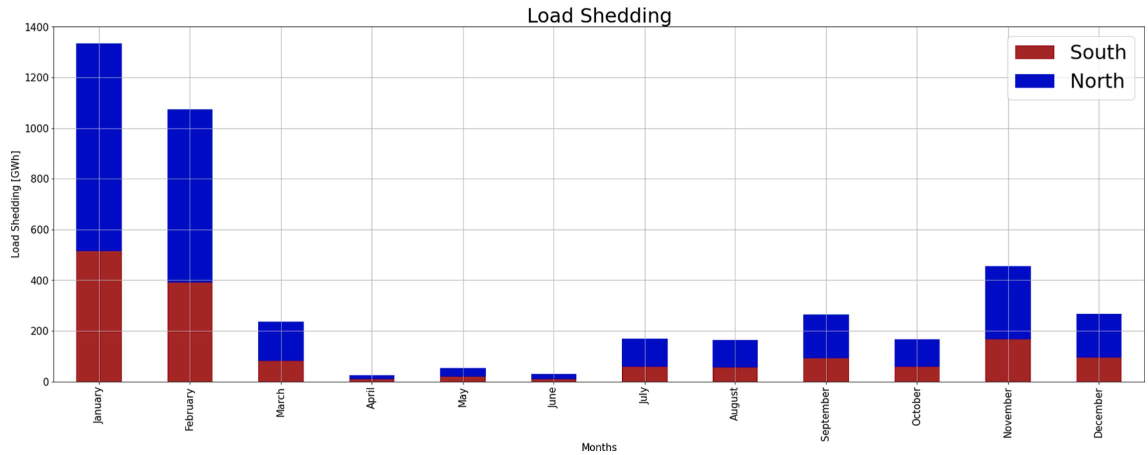

Fig. 13. Load shedding occurrence over months and regions in 2050.

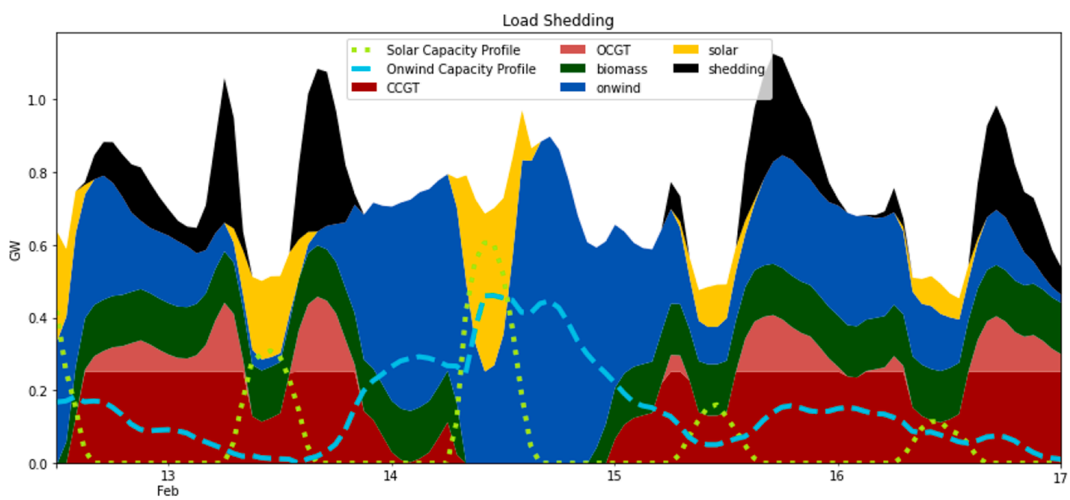

Fig. 14. Load Shedding case in the south of Germany.

conventional energy sources with additional 11 GW and 10 GW, respectively. Biomass and ror were constantly present in the system. Nearly 19 GW of Offshore wind was added from both AC and DC technologies. Solar and onshore wind were massively invested in, with an additional capacity of 66 and 78 GW, respectively. This huge addition of renewables over this period is due to the lack of conventional sources that covers the basic load, which were limited by the CO_2 emissions.

In 2050, nearly 60 TWh of both CCGT and OCGT were still present in the system, with only 1 TWh of OCGT due to its high CO_2 emissions factor. 19 TWh of biomass along with 20 TWh of ror were as well penetrated in the energy mix. Renewables were the core factor in the energy mix, with 75 TWh of offshore wind, 189 TWh of solar and 368 TWh of onshore wind.

As seen in Fig. 10, in the last 2 years, nearly 54 GW of onshore wind and 45 GW of solar were added in the last 2 years. Meaning that more than two thirds of the whole addition in the 10-year span were only added in those two specific years. AC offshore faced also a huge investment in the last 2 years, where before that the total power was nearly zero, and by the end it was nearly 12 GW.

The reason behind this huge investment was that, in 2049, CCGT share in the energy mix sharply dropped 20 TWh from the previous year, and 10 TWh in the last year, with OCGT share also decreasing 7 TWh compared to 2048, and 16 TWh decrease in the last year. This huge and unanticipated drop of the generation that covers the base load led to the huge investment of renewables in the last 2 years. Not to mention, the investments in solar and onshore wind in earlier years were decommissioned at the same last 2 years (17 GW of solar and 5 GW of onshore wind). On top of that, the biomass share of the energy mix dropped nearly 40% within this period, as the model did not see a need to reinvest in biomass plants when they were decommissioned earlier.

Looking at the cumulative CO_2 emissions from the network (Fig. 11), it can be seen that gas technologies reduce the system emissions enormously as they took place instead of the phased-out coal and lignite. Moreover, from the coal phase-out year till the last 2 years, the cumulative emissions of the system were far below the emissions limit as a result of the higher penetration levels of renewables and lower emissions, relatively. However, in the last 2 years, as the CO_2 limit went lower than the actual cumulative emissions, huge drops of OCGT occurred as they have higher CO_2 emissions factor along with a milder drop in the CCGT, with a 95% and 33% drop of their values in the previous year, respectively. This drop in the base load generation technologies was the main reason behind the massive renewables investment in the last 2 years.

More to that, in the last year, due to the huge drop in OCGT, CCGT replace this drop due to their lower emissions factor. Therefore, a huge investment in CCGT was added to the system with an investment of 10 GW. Another reason for this addition is the massive mismatch between renewables generation and demand. As the system lacks flexibility options such as storage or demand side management, and not enough biomass or ror generation was available, this leaves the model with only two options, either an investing in CCGT which generation is to a certain point limited, or a higher cost load shedding. Transmitting the energy

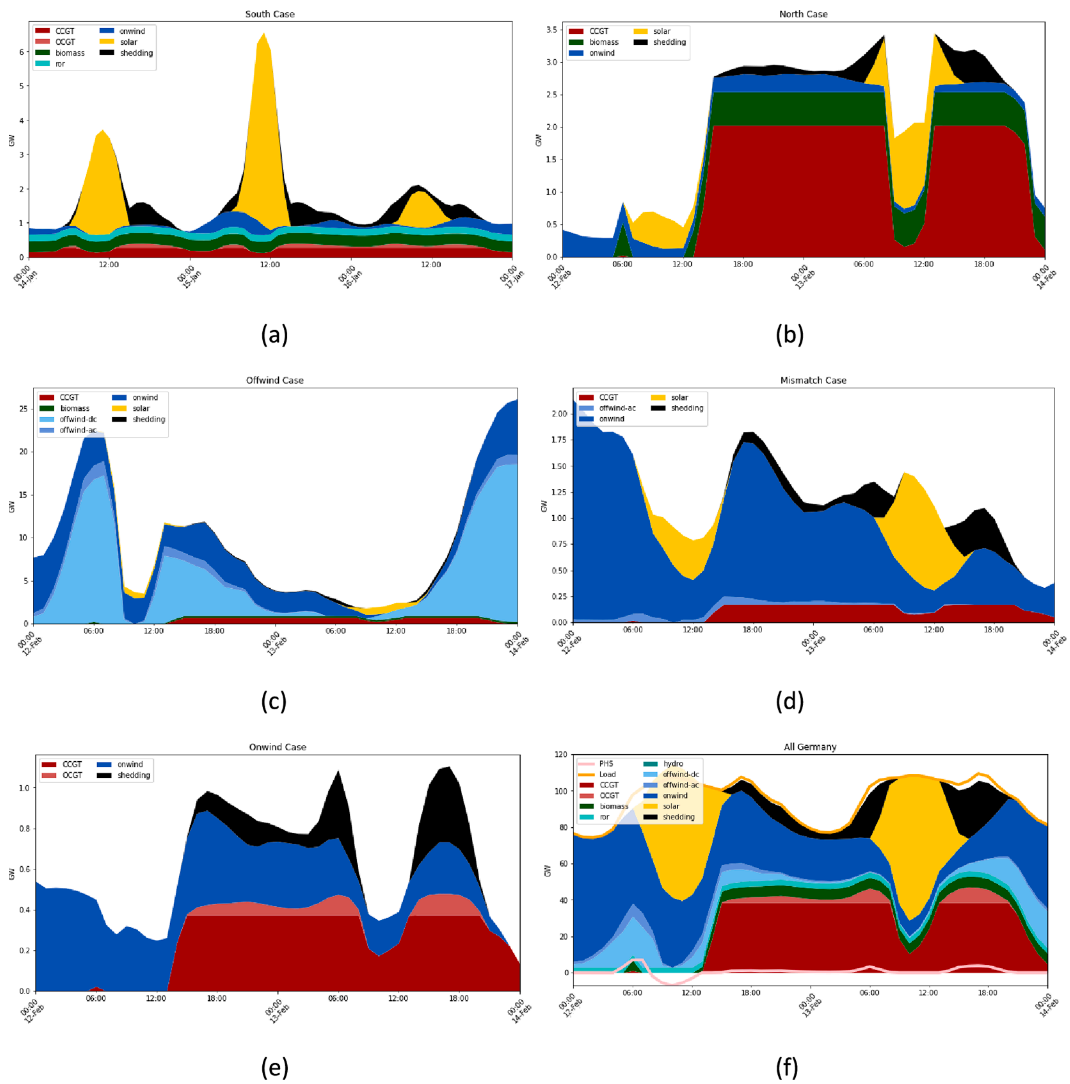

Fig. 15. Different unit commitment cases of 2050 N scenario. (a): Southern node case with load shedding and limited onshore wind availability, (b): Northern case with solar and onshore wind and load shedding, (c): Case with offshore wind as a base-load generation, (d): Generation-load mismatch case, (e): Northern case with no solar generation and load shedding, (f): The overall system case with storage and load shedding.

from other nodes did not satisfy the demand, as all nodes have, roughly, the same weather profile, and investing in other technologies with a better capacity profile was limited by the maximum yearly and regional installation rates. This issue is visible in an hourly resolution network, as the unit commitment is in charge of meeting the demand, where in daily resampled networks, the hours of enormous lack of renewable generation are outweigh by the temporal aggregation.

As a result, in 2050, 4 TWh of the load is being shed, resulting in 0.5% of the load being completely shut off. This is due to the yearly and regional limitations of investments, the renewables generation and demand mismatch, along the CO_2 emissions limitation. This means, that only in the last 2 years, an allowed higher value of yearly and regionally investments would avoid or reduce the load shedding, as more transferable energy from other generation technologies can be invested in to cover areas that needs more energy.

From a regional point of view, Fig. 21 (b) and (d) shows that 23 and 18 nodes have either already reached their maximum technical installable potential or have very little potential left for solar and onshore wind, respectively. In the case of solar installations, most of those nodes lie in the states of Baden-Württemberg, Bavaria and Rhineland-Palatinate, which together form the south and south-west part of Germany. The contrary for onshore wind, where most of those nodes are in the states of Lower Saxony, North Rhine-Westphalia, Schleswig-Holstein, Mecklenburg-Vorpommern, all of which form the northern part of Germany. More to that, looking at Fig. 12 d, a pattern can be concluded amongst those nodes, which is that they represent the nodes with the highest capacity profiles in Germany and highest technical installable potential. In other words, most of the good locations for solar and onshore investments are already exploited to the max by 2050, or being invested in this year.

In the middle and some eastern parts of Germany, very small levels of investments were made in solar or onshore. This behaviour is due to multiple reasons, most importantly due to the small electrical demand in these regions, which was covered locally by these investments. Moreover, the very high cost of grid expansion limited the need of expanding the grid infrastructure in this region or investing to move the energy to the southern regions. Not to mention, some nodes in this region have a relatively very small technical installable potential, which limits the investments in these regions. In some locations by 2020 (Fig. 12 a), especially in the middle of Germany, the nodes had already solar and onshore investments from previous years. However, when decommissioned, reinvesting in them was not the most feasible decision to make. That is the reason behind those investments being completely taken out of the system (Fig. 12 c and d).

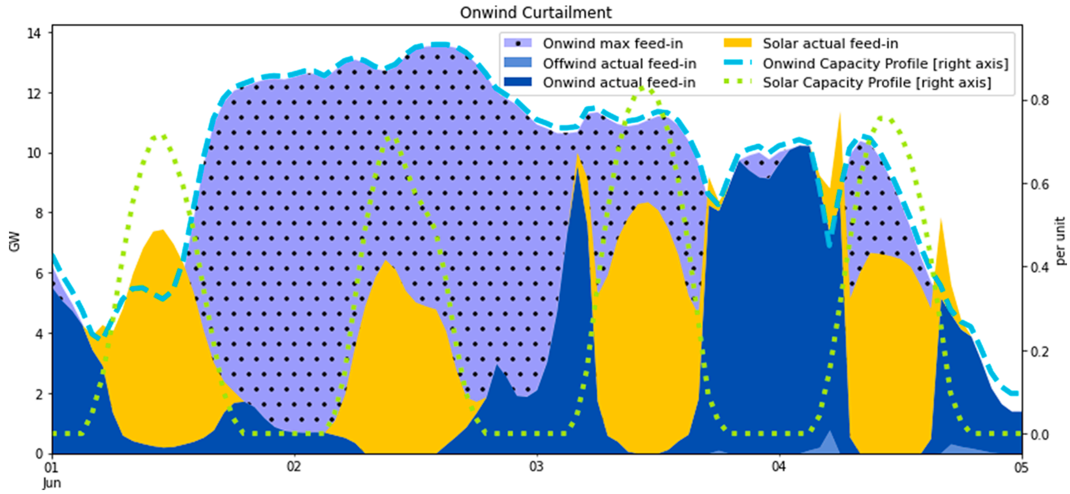

Fig. 16. Wind energy curtailment in 2050 N scenario.

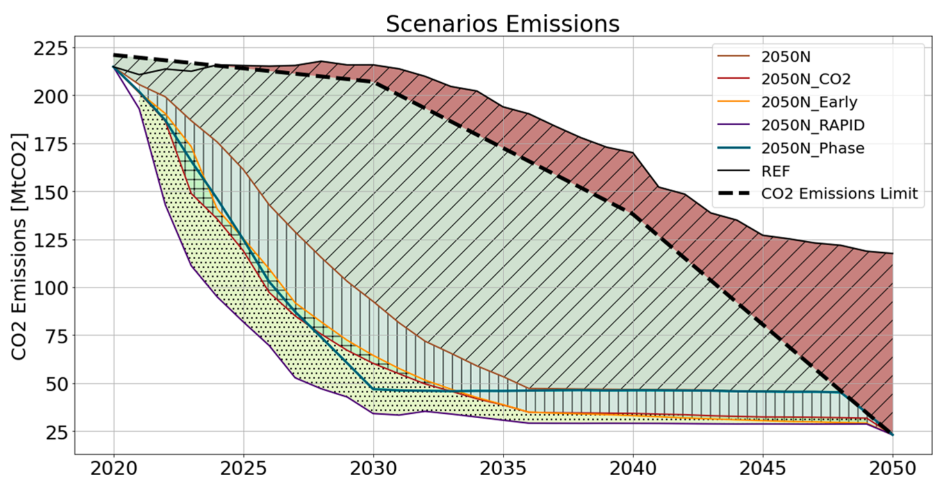

Fig. 17. Cumulative scenarios emissions.

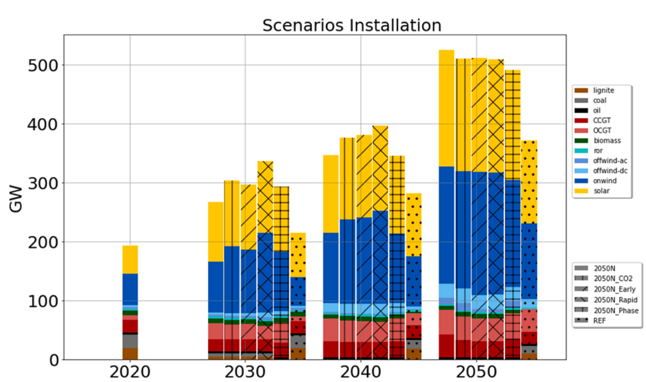

Fig. 18. Scenarios installations over the years.

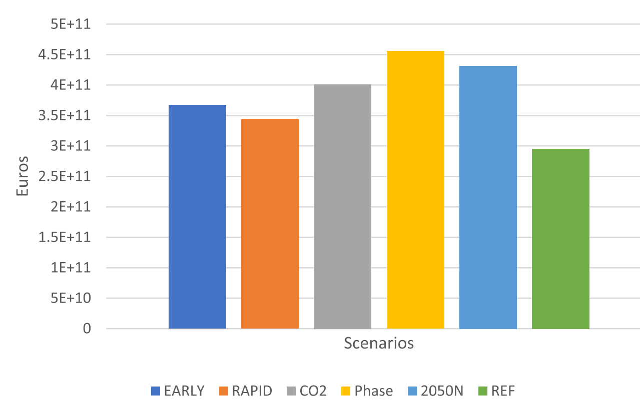

Fig. 19. System Costs without CO_2 Emissions

Looking at the load shedding issue in Fig. 13, it was found that most of the northern buses were responsible for it, especially in cold weather months. The direct reason behind it is that, most of the northern buses have a worse capacity profile for solar compared to the south. Moreover, not enough capacity could have been added to cover the demand in some regions due to the regional installation limitations and the myopic foresight. Additionally, winter months have relatively lower capacity profiles for renewables and higher electrical demand compared to summer.

However, the mismatch between generation and demand times, especially for solar, resulted in some nodes in the south being left out without taking advantage of the high installable potential and superior capacity profiles. Subsequently, this led to load shedding as shown in Fig. 14, where restricted gas could have not been used, not enough biomass or ror to cover the demand, with the absence of storage technologies, the load is being shut off in some hours when no other option

Table 9
CO_2 cumulative emissions amongst all scenarios.

Scenario	CO_2 cumulative emissions [$MtCO_2$]
2050 N	2716
2050N_CO_2	2110
2050N_Early	2170
2050N_Rapid	1677
2050N_Phase	2295
REF	5590

was available for the system.

Moreover, although the network has a limited amount of PHS and hydro storage, it helped the nodes to maximize the utilization of the renewables in those nodes along with minimal load shedding values. That is the reason behind having some nodes in the south where the capacity factor is high, the installable potential is at its maximum value, but not used at all, where neighbouring nodes are fully employed by renewables. This is visible by the fact that 11 of the nodes that reached already their maximum potential are actually nodes that have storage capacity. Additionally, due to the high share of storage capability in the south-west region of Baden-Württemberg, it can be seen that this region was the main drive for renewables investments, especially in solar power.

Examining some of the extreme cases at nodes with the highest load shedding or lowest and highest share of some renewable technologies in the north and south of Germany. It can be seen from Fig. 15 that load shedding is the only option left for the model when not enough renewables are available. This can be due to multiple reasons, such as the allowed installation potential at some nodes (a) even with renewables maximum infeed, the available installed capacity (e) or the capacity factor (b) (d) of the technology itself. When solar or wind energy goes out of the mix, due to its capacity profile at some specific times, with the gas not being able to produce more energy as it is restricted by the CO_2 limit (a) (b) (e) or not available in that node (d), biomass and ror technologies are producing their maximum energy (a) (b), a huge load shedding occurs as the load was impossible to cover.

Moreover, base load generation technologies such as gas or biomass are curtailed during peak times of generation for renewables due to their high cost and CO_2 emissions, for the case of gas generation. However, in some cases, offshore wind technology, especially DC wind, helped to cover massive parts of the load it has a very good capacity profile in some locations (Fig. 15c), where only little backup plants were employed to cover the generation shortages. On the contrary, other offshore locations suffered from bad weather conditions at some times (Fig. 15d), without having the ability to compensate for the generation shortages by either gas, biomass or hydropower, resulting again in shedding the load. This shows that offshore wind can be, up to a certain extent, operated as a base load generation in good locations if higher investment rates were enforced into the system.

Looking at the energy mix of the whole country as in (Fig. 15f) shows that, with the restricted usage of gas generation, insignificant biomass and hydro generation availability, and temporary behaviour of renewables generation along with the limited storage capability of the system (Pumped-Hydro-Storage), load shedding is left out as the only option to the model regardless of its very high cost of 100 Euros/kWh.

Another aspect of the results is the energy curtailment, as a huge investment in renewables was done over the planning horizon, especially due to certain hours where a shortage of one technology, i.e. solar, was compensated by a massive installation of other technologies, i.e. onshore wind. Therefore, enormous curtailed energy occurred, especially for onshore wind. In numbers, this curtailment was mainly due to synchronized maximum generation capabilities of solar and onshore wind as in Fig. 16. This goes hand in hand with the absence of storage and flexibility measures in the network, resulting in huge energy curtailment as the model prefered solar energy over any other technology due to its lower marginal cost. Adding to that, since the model is inelastic, meaning that the demand has to be met simultaneously by the generation, a great deal of available energy is being shut down.

7.2. Key aspects of other scenarios

In this 2050N_CO_2 scenario, the huge investments in CCGT in the last year were less intense compared to the 2050 N scenario, which is mainly due to the fixed CO_2 emissions from the system so early (Fig. 17), meaning that more CO_2 emissions were saved throughout this scenario as a cumulative value over the 30 years. However, the massive installation in the last year of offshore and onshore wind along with solar are still present, due to the sharp drop of gas share in the energy mix over the last year (20 TWh drop). In other words, the gas generation share dropped only in the last year.

Having a dynamic CO_2 tax that increases sharply in the first 10 years encouraged an earlier high investment in renewables, especially solar

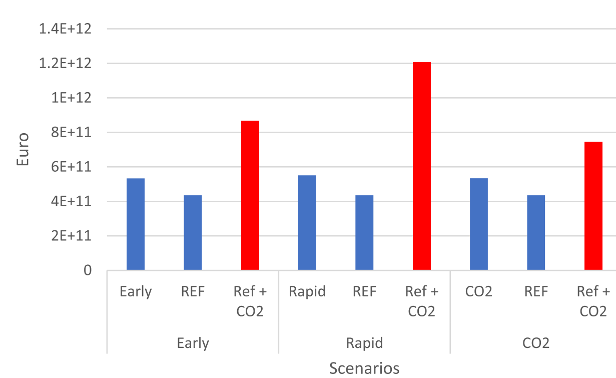

Fig. 20. CO_2 allowance impact of total system cost

Table 10
Load shedding readings in all scenarios in 2050.

	Total Wind Curtailment [TWh]	Total Solar Curtailment [TWh]	Total Shedding [TWh]	Maximum Occurring Shedding [MWh]	Time of Maximum Shedding	Wind Curtailment at Maximum Shedding [MWh]	Solar Curtailment at Maximum Shedding [MWh]
2050 N	190.6	41.5	4.0	1210.5	15/01/2050 16:00	2932.8	0.0
2050N_Phase	183.3	40.7	11.4	1363.7	15/01/2050 16:00	2753.4	0.0
2050N_CO2	196.7	40.7	0.5	22.2	13/02/2050 16:00	1563.8	0.0
2050N_Early	209.9	41.6	0.0	0.0	14/01/2050 16:00	2271.7	0.0
2050N_Rapid	207.6	41.5	0.0	0.0	15/01/2050 16:00	2426.2	0.0
REF	58.4	6.7	0.0	0.0	13/02/2050 17:00	387.2	0.0

and onshore wind as they were the cheapest options to invest in, with around 6 GW/a for both technologies, wherein the remaining 20 years, this average installation rate dropped to around 4 GW/a, even with including the massive installation in the last year (Fig. 18). The high CO_2 tax urged the maximum use of biomass, despite its highly expensive capital cost, its marginal cost was a lot cheaper than other conventional technologies. Therefore, biomass was fully reinvested in and utilised in the system. More to that, biomass reaches its maximum share of the energy mix around 2030, where the CO_2 allowance cost was very high making biomass the most favoured base load generation technology, yet very expensive compared to renewables. However, not enough renewables were integrated into the system to reduce the biomass share, which as a result was reflected in the total system cost (Fig. 19).

Furthermore, no load shedding occurred in the system, mainly due to the higher earlier investments in renewables, and to the high presence of biomass, which contrary to the renewables, can be fully utilized at any moment to cover the load at time of renewables shortages. From a regional point of view, in the 2050N_CO_2 scenario, 27 and 20 nodes have either already reached their maximum technical installable potential or have very little potential left for solar and onshore wind, respectively. Moreover, those buses were located in the south for the case of solar and north for onshore wind, meaning that most of the best locations are fully utilized in the most feasible way possible.

More to that, having a more expensive CO_2 allowance cost by 2050 helps to reduce the sharp and sudden investments, as in the 2050N_early scenario, where gas investments in the last year were no longer happening in this scenario. This also means that the share of energy from gas technologies being dropped in the last year was smoother than previous scenarios. In the last year only, high investments in renewables were added to the system due to the high CO_2 reduction. However, offshore AC was not highly invested in due to the less drop in gas generation in the energy mix. In other words, in the previous scenarios, the gas share was relatively higher in all years as it was beyond the CO_2 limit and cheap to use. This however is no longer valid in this scenario, as it gets extremely expensive, gas share of the energy mix was reduced earlier and only used at times of renewables shortages. Nevertheless, a drop gas generation drop occurred in the last year, which mainly caused a sudden high investment rate in renewables, especially solar and onshore wind, but load shedding was not needed in this scenario, as the system was to a certain point prepared for the last year extreme demands. Moreover, gas technologies suffered from a very low FLH as they were extremely expensive (Table 12), with a CO_2 emission factor, especially in the case of OCGT as it has higher marginal cost and emissions factor. In other words, the model gave priority to all other technologies and gas was left out as the last choice to generate from. Solar and onshore wind have very good FLH values, but offshore wind suffered from a very low FLH, mainly due to its relatively high marginal cost, where it was only preferred when there was no solar or onshore wind available.

From a regional point of view, in the 2050N_early scenario, 29 and 22 nodes have either already reached their maximum technical installable potential, or have very little potential left for solar and onshore wind, respectively. Meaning that more installable power in many of the regions in Germany were better utilized.

Relatively speaking, having an earlier and expensive CO_2 allowance cost helps to smoothen the energy transition as it suffers less from the investment spikes. This was seen in the 2050N_Rapid scenario. Although the case of extreme investments occurred in the last year due to the same aforementioned arguments, but enormous installation rates occurred at the beginning of the planning horizon helped to reduce the spike at the end of the optimization period. This is mainly due to the extremely expensive CO_2 emissions tax of 200 Euro per MtCO_2 enforced by 2030. The installation rates for onshore wind and solar energy in the first 10 years were 8 and 7 GW/a, respectively. Where the factor decreased by around 3.5 GW/a for both technologies in the following 20 years. Moreover, what helped to smoothen the sudden spike of investments was as well the relatively smaller shares of gas participating in the energy mix. In other words, in earlier years, the system avoided relying on high shares of gas due to its extremely high marginal cost. Therefore, less intense gas generation drops and smoother investment in renewables occurred.

The 1.5-degree-target could be realised by having CO_2 limits orientating on the goals of the federal government, with a sharply increasing CO_2 allowance cost, and a coal phase-out. Looking at the cumulative emissions from all scenarios (Fig. 17) and (Table 9), it can be seen that the earlier and higher the CO_2 allowance cost, the less the system emissions will be. However, the actual emissions reduction targets are not enough by 2050, where the system emissions will be around 23 Mt CO_2, which does not go in line with the 1.5-degree-target of having zero emissions from the energy system by 2050.

Moreover, having an earlier phase-out without the high CO_2 allowance cost will not be the best solution in terms of system emissions, as it was observed from the 2050N_phase scenario, where an earlier phase-out by 2030 with a fixed emission price emitted more than the other CO_2 scenarios with a phase-out date by 2038 and a dynamic CO_2 allowance cost.

Having no clear policy, without a CO_2 allowance cost and a phase-out date will result in the cumulative CO_2 emissions exceeding the CO_2 budget of the country, as it was observed in the REF scenario. Comparing all scenarios together, it can be summarized from Table 9, a huge CO_2 saving is possible in all scenarios except the REF scenario, where the cumulative CO_2 emissions exceeded the budget by around 1390 Mt CO_2. This difference is further explained through Fig. 17, where a rapid and sharp CO_2 allowance cost is the optimum solution for staying in line with the 1.5-degree-target.

Comparing the load shedding amongst all other scenarios, it can be seen in Table 10, that the load shedding heavily occurred in the two scenarios that represent the current emissions policy. The reason behind having load shedding is due to a combination of factors such as the myopic foresight as well as the regional and yearly limits. In this combination, mostly in the year 2050, load shedding is needed resulting from insufficient RES investments in prior years and reaching the annual limits in most regions. Additionally, the restrictions on using gas technologies and the limited transmission grid capacity have caused these extreme conditions. Load shedding could be avoided with large grid investments or flexibility. However, introducing a CO_2 tax incentivized an earlier and higher investments in renewables, without the need of higher investments in 1 year, which eliminated the load shedding. This comes as a fundamental proof of the inevitability of introducing a CO_2 tax to the energy system, and as an alarming indication about the current emissions policy.

Looking at another aspect of the scenario settings, which is the earlier phase-out of coal-fired power plants, more investments in OCGT were implemented at the beginning to compensate for the early phase out of coal and lignite, this was mainly due to the less expensive capital cost compared to CCGT. This encouraged the model not to heavily reinvest in decommissioned biomass plants. However, a huge drop of OCGT gas share occurred in the last year, which took OCGT completely out of the energy mix. The main reason behind it is that, earlier investments made the actual CO_2 emissions way less than the maximum limit, which stayed fixed until the last 2 years when the maximum limit decreased, forcing the model, somehow, to completely take OCGT out of the mix. Moreover, huge investments in renewables, especially solar and onshore wind, were integrated in the first and the end of the planning horizon. The main reason behind it is that, in the beginning, to compensate for the rapid phase-out of coal and lignite. However, in the end, the huge investments in renewables were made to compensate for the huge drop of gas generation. This massive drop in the base load generation technologies, with the relatively fewer renewables investments compared to other scenarios, led to a huge load shedding of 11 TWh in the last year.

The high CO_2 allowance cost is reflected through installation in the three CO_2 scenarios, where in the first 20 years more installations were done, after which less intense installation rates occurred in comparison with the 2050 N scenario. In the earlier phase out scenario, more gas was integrated into the system in the first 10 years to compensate for the coal and lignite, which is reflected through the road map with fewer renewables installation, respectively. In the REF scenario, as coal and lignite were still present in the system, nearly 120 GW less installations of renewables happened to the system, along with less gas technologies investments. However, more full load hours were utilized in this scenario due to the presence of base load generation technologies. See Table 12 in Appendix B.

The total system cost of the scenarios in Fig. 19 presented various aspects of how the system operation was reflected in terms of costs. For instance, the early-phase scenario was the most expensive scenario due to the higher and earlier investments rates and compensation of lignite and coal, not to mention the high utilization of biomass in the system. The 2050 N scenario was the second most expensive scenario, mainly due to the investment spikes in the last 2 years and the huge addition of CCGT technology. The REF scenario was the cheapest, mainly due to the relatively small investments rates in both renewables and gas, not to mention the complete absence of biomass power plants for the last 10 years.

However, the excessive CO_2 emissions in the REF scenario come with an extra cost in reality. While the previous cost comparison is not completely true for the CO_2 allowance scenarios, as the emissions led to the high system cost. However, new outlooks appear when comparing them with the REF scenario with the same dynamic CO_2 allowance values as illustrated in Fig. 20, which clearly shows that the REF is not the most feasible solution in terms of cost, nor, without doubt, in terms of system emissions.

8. Limitations and future work

The high complexity of the model resulted in different factors interacting with each other, which highly affected the optimization process. The high spatial resolution offered in this model presents new viewpoints into the regional display of renewable energy. The myopic optimization provided a more reliable planning approach, and accounted for future uncertainties. The regional and yearly potential values presented new insights into reflecting social acceptance and regional distribution of renewables in the energy system analysis. However, due to lack of data and studies in different areas, many assumptions were made in different parts of the model, which was reflected in some results and can be unreasonably argued about. The following will highlight different points that influenced the optimization process.

The regional, and country yearly and maximum potential limits were the most significant factors to affect the optimization process. Different potential values lead to different results, huge load shedding, or infeasible models. As there was a huge lack of literature in this topic, the historical installation data were analysed and adapted to match the 2050 system, and suit its demand. However, this topic can be a field of development and further studying, so that these values will take into consideration different factors such as the CO_2 limit, social acceptance, previous installation rates, load centres, actual generation potential, region, and network clustering.

The model in this study was left with the choice to employ renewables or conventional power plants, to try to represent real system operation of redispatch. Nevertheless, to enable a quicker energy transition and a shift towards a neutral electricity system, curtailment of the renewable energy has to be reduced to the minimum, and a priority option for the renewables should be enabled in the model.

More points on enhancing the credibility of the model can be achieved through interconnecting the system with its surrounding grids, and enabling energy exchange. On the one hand side, this can lead to enhancements in the display of flexibility needs, due to a larger balance area. On the other hand, the energy system development in surrounding countries is unclear, which would lead to the necessity to include these countries in detail within the model and in consequence limiting the detailed display of the German energy system due to computational limits. Flexibility measures in the demand (Demand-Side Management) and generation (long/short-term storage and CCS) are to be integrated in the model, to increase the plausibility of the model.

Nonetheless, different general assumptions were made on different networks, such as the load increasing factor, which was assumed to be equal in all regions of Germany, where in reality load centres are located more to the south of the country and are expected to face higher increases than the northern region.

Finally, one of the main drawbacks of the model was that the model satisfies the CO_2 limit without looking for a room of improvement, even though more renewable can be employed in the system. Moreover, the optimization process is done on a yearly basis without taking into consideration what will the model look like 2 or 3 years later in the future. A hybrid myopic and perfect foresight model can highly affect the results of the model and make it more credible.

9. Conclusion

The study concluded different road maps and paths for the energy system in Germany, with insights on which technologies should gain more focus and research in the next 30 years.

Solar and onshore wind will play a major role in the energy mix of the future, even with the absence of an energy policy, as in the REF scenario. This is mainly due to their low LCOE compared to the conventional power plants. However, the historical regional and yearly investments trends will not be enough to achieve climate neutrality by 2050. From the conventional power fleet, although focusing the investments on CCGT might result in higher capital cost, more CO_2 emissions can be saved, and less investments spikes will occur.

From a regional point of view, the good locations for solar and onshore wind in the south and north, respectively, need to be fully utilized. However, not only good locations are used within the system, meaning that renewables investments will be done relatively everywhere in Germany. High energy curtailment occurred due to the system's unit commitment. More to this point, higher regional investments values in the good location will increase their shares, and help the system during bottlenecks. The same applies for the yearly investment limit, which might as well reduce the total system cost by avoiding the investments of higher capital cost renewables, such as offshore wind.

The study showed clearly that offshore and run-of-river technologies can operate as a base-load generation units. However, the regional yearly installation potential restrains the offshore wind usage, as no more investment can be made. Biomass power plants proved their capability of helping the network in congestion cases. However, as the model is optimizing with myopic foresight, some plants were decommissioned earlier and not reinvested in, even though they were needed later in the planning horizon.

The results showed that the earlier coal phase-out is not the most promising action in the energy transition, where the model simply replaces coal by gas technologies. With the current emission reduction strategy, the country's CO_2 budget will be exceeded, and it is greatly doubtful to achieve the 1.75 degree-target, let alone the 1.5-degree-target. Introducing a CO2 allowance cost helped reduce the cumulative CO_2 emissions, especially with a rapid increase of emissions tax, the cumulative CO_2 emissions were reduced to stay in line with the 1.5-degree-target, which comes as a proof of the inevitability of introducing a higher and sharply increasing emission tax. Moreover, applying higher CO_2 allowance cost will overturn the conventional power plants and focus on renewables investments.

The results and scenarios in this study give an insight on how the future German power system may look like. A better path can be developed from this model to reach a climate-neutral energy system and conform with the 1.5-degree-target. A huge research potential still lies in this model, which will highly affect this path and insight. More scenarios can be studied on this model to have different ideas on how the model will react, and more technologies and degrees of innovation will be presented to the model to have a smoother path towards achieving the climate goals of Germany.

CRediT authorship contribution statement

Anas Abuzayed: Conceptualization, Methodology, Software, Validation, Investigation, Formal analysis, Writing – original draft, Data curation, Visualization. **Niklas Hartmann:** Conceptualization, Funding acquisition, Project administration, Supervision, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Appendix A

Symbol	Description
∂	Electric Demand
I	Year
Fd	Demand increase/decrease factor
Fc	Cost increase/decrease factor
$\mathscr{M}_t$	Maximum technical potential
$\mathscr{M}_r$	Maximum regional potential
$\mathscr{M}_y$	Maximum yearly potential
G	Generation technology
N	Network node
ε	Newly added capacity
ι	Element lifetime
Ϫ	Existing capacity
κ	Annualized capital cost per unit capacity
ϫ	Dispatch of existing generation capacity
o	Marginal cost per unit dispatch
ε	Dispatch of newly added generation capacity
Ȿ	Fixed capacity of current grid infrastructure
N	Added capacity of grid infrastructure expansion
$\mathscr{L}$	Branch
Ü	transmission technology
ῶ	Weather dependant availability
℮	Emissions limit
H	thermal efficiency
Ⅎ	Emission factor per MWh_{th}
s	Storage technology
Ƕ	Storage dispatch
T	Time
ɕ	Storage technologies state of charge
Ƭ	Fuel cost
Γ	Load shedding
Abbreviation	**Description**
CCGT	Combined-Cycle Gas Turbine
CCS	Carbon Capture Storage
CF	Capacity Factor
CO2	Carbon Dioxide
EEG	Erneuerbare-Energien-Gesetz (German Renewable Energy Law)
FLH	Full-Load Hours
H2	Hydrogen
OCGT	Open-Cycle Gas Turbine
OPSD	Open Power System Data
p.u.	Per unit
PHS	Pumped Hydro Storage
RES	Renewable Energy Sources
ror	Run-of-River

Appendix B

Tables 11 and 12 Fig. 21

Table 11
Sample of mapped renewable energy plants.

	yead_added	year_removed	carrier	…	latitude	longitude	bus
0	1995	2020	solar	…	0.86	0.122	DE0 1
1	1995	2020	solar	…	0.918	0.239	DE0 11
2	1995	2020	solar	…	0.885	0.197	DE0 9
3	1995	2020	onwind	…	0.927	0.211	DE0 7
4	1995	2020	solar	…	0.851	0.166	DE0 15
…	…	…	…	…	…	…	…
1,872,551	2019	2044	solar		0.852	0.176	DE0 15
1,872,552	2019	2044	solar	…	0.869	0.174	DE0 4
1,872,553	2019	2044	solar	…	0.897	0.158	DE0 12
1,872,554	2019	2044	solar	…	0.877	0.163	DE0 4
1,872,555	2019	2044	solar	…	0.843	0.138	DE0 3

Table 12
Scenarios FLH over the optimization years.

		coal	lignite	CCGT	OCGT	biomass	ror	offwind-ac	offwind-dc	onwind	solar
2050 N	2020	4884	8200	135	0	1178	8760	4071	4781	2564	1151
	2030	7690	8529	3090	546	5475	8739	3156	3798	2669	1170
	2040			3410	620	5375	8754	2215	2932	2409	1163
	2050			1770	0	3301	8725	1048	1678	1921	1098
CO_2	2020	4884	8200	135	0	1178	8760	4082	4769	2564	1151
	2030	4744	5770	2124	345	5615	8739	2306	2954	2422	1166
	2040			2666	468	4570	8751	1752	2384	2207	1153
	2050			1483	122	3126	8731	994	1622	1894	1101
Early	2020	4884	8200	135	0	1178	8760	4079	4773	2564	1151
	2030	5037	6103	2294	377	5827	8736	2513	3067	2469	1167
	2040			2579	451	4468	8743	1740	2290	2179	1152
	2050			1695	296	3101	8738	1027	1542	1832	1096
Rapid	2020	4884	8200	135	0	1178	8760	4077	4774	2564	1151
	2030	1033	1598	2754	242	4633	8739	1659	2295	2200	1159
	2040			2288	397	4113	8742	1577	2040	2086	1147
	2050			1691	295	3104	8745	999	1563	1845	1096
Phase	2020	4941	8231	135	0	1178	8760	4080	4772	2564	1151
	2030			3777	699	6053	8734	2691	3263	2521	1167
	2040			3393	621	5378	8753	2251	2963	2421	1163
	2050			1907	0	3392	8719	1124	1747	1960	1101
REF	2020	4543	7715	135	0	1178	8760	4074	4777	2564	1151
	2030	5763	8215	610	23	2684	8741	4078	4747	2942	1173
	2040	5096	7003	1800	281	3722	8760	3385	4216	2761	1178
	2050	4618	5753	2529	484	3941	8759	2376	3169	2414	1163

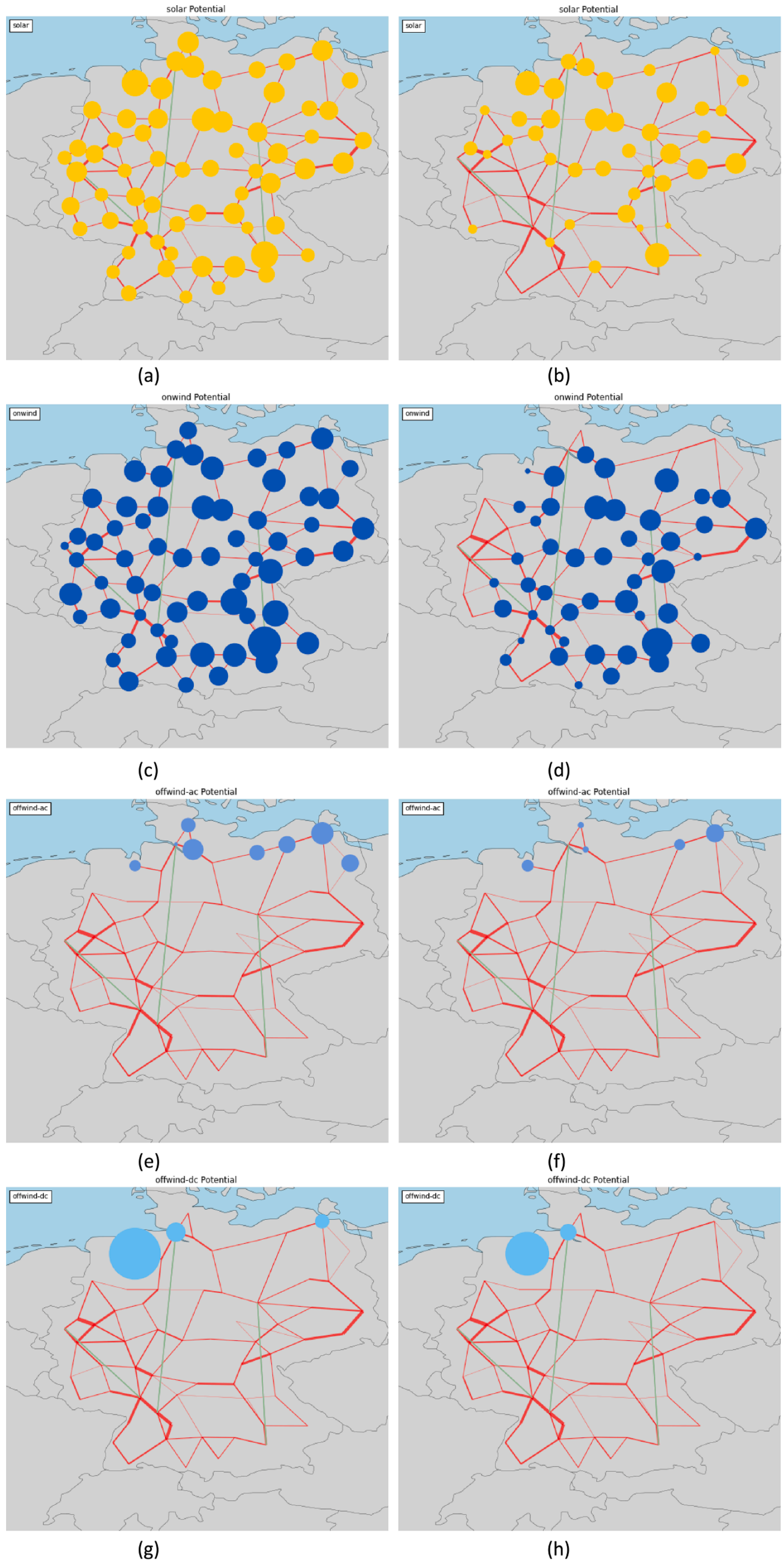

Fig. 21. Technologies maximum technical potential in 2020 and 2050 for the 2050 N scenario.

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