Documentation of LIMES-EU - A long-term electricity system model for Europe

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This document presents a detailed documentation of LIMES-EU – the Long-term Investment Model for the Electricity Sector of Europe. LIMES-EU is a linear optimization model that simultaneously optimizes investment and dispatch decisions for generation, storage and transmission technologies. Its integrated approach together with an intertemporal optimization from 2010 to 2070 allows for analysing comprehensive scenarios on the cost-effective future development of the European power system and the European Union's Emission Trading System (EU ETS). In this version, we added a bottom up representation of the steel module, which allows to provide more details on the technology, pace and location decisions of new investments.

Despite the model's long-term focus, LIMES-EU effectively accounts for the short-term variability of electricity demand and the renewable energy sources wind and solar. In order to provide transparency, this documentation gives a detailed overview of the model's underlying assumptions, its input data and a full list of the model equations.

This model documentation is still largely based on the 2014 documentation (Nahmmacher et al., 2014).

Version log

Date	Version	Changes	Link
October 2014	--		https://www.pik-potsdam.de/research/transformation-pathways/models/limes/DocumentationLIMESEU_2014.pdf/view
December 2018	--	New technologies (hydrogen, waste, oil, other gases, batteries, electrolysis); vintages for gas, lignite and hard coal; updated technology parameters (e.g., fuel costs and RES investment costs); updated 2020-2050 demand forecast; transmission and generation capacities in 2015 fixed; reference transmission capacities for 2020 and 2030; updated potential for vRES and hydropower; implementation of a robustness constraint (de-rating factors specified); comparison between model and historic data updated to 2015; implementation of carbon price floor	https://www.pik-potsdam.de/research/transformation-pathways/models/limes/limes-documentation-2018
April 2020	2.35	New technologies (BECCS); updated parameters (e.g., PV costs and fuel costs); adjustment of vRES availability factors; adjustment of hourly patterns bases on historic peak demand; new references NTC for 2020 and 2040; updated demand forecast; bounds on transmission and generation capacity in 2020; storage costs split into power and reservoir costs; additional calibration details (e.g., adjusting 2020 demand and capacities); additional test for model robustness (e.g., impact of representative days modelled on results); implementation of reserves; implementation of MACC for the energy-intensive industry; implementation of the MSR; elaboration on the EU ETS modelling (e.g., assumptions for aviation and heating).	https://www.pik-potsdam.de/research/transformation-pathways/models/limes/limes-documentation-april-2020

Date	Version	Changes	Link
May 2020	2.36	Proxy for hydrogen storage capacity (able to provide seasonal storage); updated costs for pumped storage plants and hydrogen storage; updated installable capacity for hydropower	https://www.pik-potsdam.de/research/transformation-pathways/models/limes/limes-documentation-may-2020
February 2021	2.37	New proxy for hydrogen storage capacity depending on assumed cycles; improved representation of hydrogen in the model; update investment costs for wind offshore and hydrogen technologies; update biomass fuel costs; new constraint on minimum year load for certain technologies; MACC adjusted according to recent emissions and abatement costs data	https://www.pik-potsdam.de/en/institute/departments/transformation-pathways/models/limes/model-documentation-v2.37
March 2023	2.38	Update investment costs for Gas GT, Oil, Hydrogen CT; update electricity demand; new module for maritime sector; new representation of myopia	https://www.pik-potsdam.de/en/institute/departments/transformation-pathways/models/limes/limes-documentation-v2-38-march-2023

Date	Version	Changes	Link
November 2024	2.40	Updated investment costs, fixed O&M and lifespan for variable RES; updated techno-economic parameters for thermal power plants and hydropower; updated fuel prices, updated costs for electrolysers; updated techno-economic parameters for cross-border transmission; new section for direct air carbon capture and storage assumptions; updated electricity demand assumptions; updated generation and transmission capacities for 2020; assumptions on short-term capacity additions for nuclear and coal plants; new section on biomass potentials; new section on how MACC for aviation and maritime sectors are derived; updated comparison of historic and modelled emissions to 2020; overall cleaning of outdated modules.	https://www.pik-potsdam.de/en/institute/departments/transformation-pathways/models/limes/documentation-of-limes-202411_vf-1.pdf
August 2025	2.50	Revised investment costs for all technologies, updated fuel prices, fixed generation and transmission capacity in 2025, updated investments in nuclear capacity; new steel sector module.	https://www.pik-potsdam.de/en/institute/departments/transformation-pathways/models/limes/documentation-of-limes-202508_vf.pdf

Contents

1. Introduction

The Paris Agreement demands strong actions to decarbonize the electricity systems. In Europe several policies are in place intending to reduce emissions, namely national renewable support and the European Union's Emission Trading System (EU ETS). However, there are still numerous open questions of how to achieve a strong transformation of the electricity system - comprising technical, economic and policy aspects while facing simultaneous pressure to decarbonize and expand to cope the increasing electrification needs. This paper introduces a techno-economic model suitable to analyse such questions called The **L**ong-term **I**nvestment **M**odel for the **E**lectricity **S**ector of **EU**rope (LIMES-EU). While the model has a clear focus on the EU electricity system, it has evolved to cover the entire EU ETS1[2] and provide insights on the decarbonisation paths and costs of all its sectors covered. Additionally, in this version we include a steel sector module -although not necessarily considered in the default scenario- aimed to provide detailed insights on its decarbonisation.

Within the framework of the European Green Deal, the European Union (EU) must reduce greenhouse gas (GHG) emissions by 55% in 2030 compared to 1990 levels.[3] and achieve climate neutrality by 2050. These targets have been translated into specific measures for the two systems covering all the economic activities, i.e., the EU ETS and the Effort Sharing Regulation (ESR) – and the soon to be deployed ETS for the ESR sectors. For instance, the EU ETS has the target to reduce emissions by 62% in 2030 compared to 2005 levels[4] and has undergone several modifications of its original scope.

[2] For simplicity purposes we refer to the EU ETS1 as EU ETS or ETS in this document.
[3] See Regulation (EU) 2021/1119 of the European Parliament and of the Council of 30 June 2021 establishing the framework for achieving climate neutrality and amending Regulations (EC) No 401/2009 and (EU) 2018/1999 ('European Climate Law')
[4] See 'Fit for 55': Council and Parliament reach provisional deal on EU emissions trading system and the Social Climate Fund (Press release, Council of the EU)

LIMES-EU follows a bottom-up approach and models the electricity sector in detail. Other EU ETS sectors– energy-intensive industry (with the option of representing in detail the steel sector), district heating, aviation and maritime – are represented through marginal abatement costs curves. Incorporating electricity generation, storage and transmission technologies, as well as abatement costs for the other EU ETS sectors, LIMES-EU simultaneously optimizes investment decisions in 5-year steps from 2010 to 2070 for each country of the EU (except Cyprus and Malta), the United Kingdom, Norway, Switzerland and the (non-EU) Balkan region considering European-wide and country-specific climate and energy targets. Despite its long-term focus, it accounts for short-term fluctuations of demand and vRES supply when determining the optimal electricity generation mix. In this way LIMES-EU delivers consistent and cost-effective scenarios for the future EU ETS, with detailed investments required in the European power system. This allows us to assess the impact of national and EU policies, e.g., the impact of updated EU ETS targets of the EU Green Deal on the power sector (Pietzcker et al., 2021). See Figure 1 for a summary of the model features.

This documentation aims to give a comprehensive and detailed description of LIMES-EU. Many of the parameters used in the model depend on future technological, economic and political developments and are therefore highly uncertain. To facilitate a correct interpretation of our model results and to provide a maximum amount of transparency, we aim to disclose all parameter values used for our default scenarios and describe the assumptions on which our parameter choice is based. A large part of the model equations as well as some calibration data did not change from the earlier LIMES-EU versions of the model. Though they are already discussed in the supplementary material of the papers in which it has been used (e.g., Pietzcker *et al*. (2021)) they are stated here again for the sake of comprehensiveness.

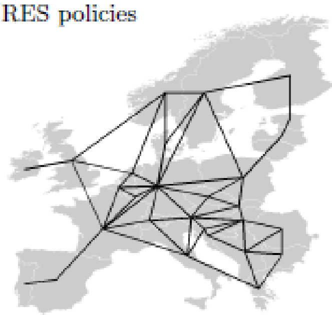
LIMES-EU - The **L**ong-term **I**nvestment **M**odel for the **E**lectricity **S**ector of **EU**rope

Type of model

linear optimization model
implemented in GAMS using the CPLEX Solver

Objective of the model

minimizing the cumulated costs of electricity provision
for a given electricity demand and exogenous CO_2/RES policies
by optimizing investment and dispatch decisions
for generation, storage and transmission capacities,
as well as emission reduction in other sectors
covered by the EU ETS such as
energy-intensive industries and district heating



Temporal scope & resolution

from 2010 to 2070 in 5-year steps
6 representative days per year
8 time slices per day
perfect foresight (by default) or myopic version

Geographical scope & resolution

Europe; 29 model regions
all Member States of the European Union (without Malta and Cyprus)
plus Norway, Switzerland, UK and an aggregated region of non-EU Balkan countries

Technologies

generation technologies
nuclear, hard coal, lignite, natural gas (combined cycle / gas turbine), oil
hard coal CCS, lignite CCS, natural gas (combined cycle) CCS, other gases
hydrogen combined cycle, hydrogen combustion turbine, hydrogen fuel cell, waste
hydro, wind onshore, wind offshore, photovoltaic, concentrated solar power, biomass
storage technologies
pumped storage power plants, batteries, hydrogen electrolysis
transmission technologies
net transfer capacities between model regions

Policy focus

RES support -> country-dependent targets
EU ETS and MSR -> energy-intensive industry and district heating represented through marginal abatement cost curve (MACC)

Figure 1. LIMES-EU in a nutshell.

The following Section gives an overview about the model and its basic functioning. Section 3 briefly presents an approach for efficiently decreasing the intra-annual resolution of the model. It allows for keeping computational demand to a minimum while at the same time correctly reflecting the short-term variability of vRES. A more detailed description of the approach is provided in Nahmmacher et al. (2016). Sections 4.1 and 4.2 discuss the standard parameter assumptions used to run the model, with Section 4.1 focusing on technology-specific parameters that are same for every model region and Section 4.2 focusing on region-specific input data. All prices and cost stated in this paper are given in 2010 prices. An overview about different climate and energy-related policies that can be implemented in LIMES-EU is presented in Section 8. Sections 9 provides more detail of the model calibration. A comprehensive list of all model equations can be found in Appendix A. Region names are often abbreviated by a two-letter code in this documentation; an explanation of the codes, which are based on ISO 3166-1, is given in Appendix B.

2. Model Overview

2.1. Objective Function

The model is formulated as an intertemporal social planner problem with perfect foresight. It minimizes the cumulated discounted costs of electricity provision for all model regions over the whole model time span simultaneously (Equation (1)). The total system costs C^{tot} are the intertemporal sum of the costs for capacity investments C_t^I, fuel costs C_t^F, operation and maintenance costs C_t^{OM} as well as possible CO_2 emission costs $C_t^{CO_2}$ of each time step t. The factor Δt accounts for the time span between two model years. A salvage value V for the capacity stock that remains at the end of the time horizon is subtracted. All values are discounted to present values using the discount rate ρ . A comprehensive list of all model equations is given in Appendix A.

$$C^{tot} = \sum_t \left(\Delta t\, e^{-\rho(t-t_0)}\left(C_t^I + C_t^F + C_t^{OM} + C_t^{CO_2}\right)\right) - e^{-\rho(t_{end}-t_0)}V \tag{1}$$

The electricity demand is endogenous to the model depending on its configuration. We assume an exogenous base demand for all countries, but some of the technologies in the model consume electricity, e.g., batteries and electrolysers, which depend on market conditions and is thus endogenous. However, the focus is on the supply side of the electricity system and its interactions with the transmission infrastructure. Using a social planner approach, the model abstracts from the nearly infinite number of heterogeneous players in the electricity sector. The social planner solution is equivalent to the outcome of a decentralized market under perfect market conditions. The model results thus show how a cost-optimal European electricity system under the given assumptions would look like, not how the European electricity system that faces considerable market distortions will evolve within the next decades. The model is formulated in GAMS[5] and uses the linear solver CPLEX.

2.2. Geographical Resolution

The current version of LIMES-EU optimizes the electricity system and abatement of the other EU ETS sectors (excluding Cyprus and Malta) plus the Balkan region, Norway, Switzerland and the United Kingdom. Except for the Balkan region, all countries are modelled as individual entities. They have different electricity demand, initial generation and storage capacities, natural resource endowments, and national energy policies. Their location is also relevant as countries are connected via an electricity transmission grid. Natural resource endowments include the availability of lignite and biomass as well as hydro, wind and solar power. Due to the country-specific resolution, energy policy targets can be set on the national level or for a specified group of model regions (e.g. EU Member States).

2.3. Temporal Resolution

LIMES-EU makes use of two different time scales. The long-term scale ranges from 2010 to 2070 and is subdivided in 5-year *time steps*. The short-term scale subdivides the time steps into

[5] General Algebraic Modelling System, http://www.gams.com.

multiple *time slices*. Eight time slices - with a length of three hours each - add up to one representative day. A weighting factor is given to each representative day; together they add up to one model year. Assigning different weights to representative days allows for representing both days with common and rare load patterns. Section 3 presents the approach of how to select these representative model days.

While investments in generation, storage and transmission capacities, as well as abatement measures in other EU ETS sectors, are endogenously determined for each of the 5-year *time steps*, the balancing of electricity demand and supply, i.e. the dispatch of generation, storage and transmission capacities, is modelled for each time slice. The short-term perspective is needed to correctly value the available investment options by accounting for the intra-year variability of the electricity demand and intermittent renewable resources.

2.4. Technologies

The following briefly introduces the technologies represented in LIMES-EU, namely electricity generation, storage and transmission, as well as carbon removal technologies. Section 4.1 provides a more detailed description of each technology. Power plants, transmission lines and storage facilities are not represented as single units in LIMES-EU, but are aggregated based on their economic and technical characteristics[6]. Modelling technology classes rather than individual units considerably simplifies the model, which otherwise could not be solved due to computational constraints.

Generation Technologies These convert primary energies to electricity. Lignite, hard coal and gas combined cycle are split in four vintages each one according to the time they were commissioned (before 1980, between 1980 and 1995, between 1995 and 2010, and

[6] e.g. all hard coal power plants of a similar age in France are aggregated to one class.

after 2010) in order to account for the technological development. Each of the four vintages are treated as an individual technology with a different efficiency. There are thus 29 different generation technologies in LIMES-EU that are classified into intermittent and dispatchable generation technologies. Wind onshore, wind offshore, solar photovoltaic (PV) and concentrated solar power (CSP) are intermittent with their availability varying both on a spatial and temporal scale. To account for intra-regional differences in wind and solar resources, the potential and availability of each technology is subdivided into three resource grades per intermittent generation technology. The availability of dispatchable technologies for each model region remains constant throughout the year. Dispatchable technologies in LIMES-EU comprise lignite, hard coal, natural gas combined cycle power plants and gas turbines as well as nuclear, biomass, hydrogen, waste, other gases, oil and hydro power plants. Electricity generation based on lignite, hard coal, natural gas, oil, waste and other gases is associated with CO_2 emissions. Optionally, lignite, hard coal, combined cycle natural gas plants and biomass can be enhanced with carbon capture and storage (CCS) technology that reduces their CO_2 emissions by storing them underground. Biomass CCS (BECCS) indeed provides negative emissions, as it is considered that its emission factor equals the carbon captured during the life of the plant. Hence, when capture is enabled, the captured emissions are accounted as negative emissions.

Transmission Technologies Transmission technologies enable the transfer of electricity between neighbouring regions. Transmission is modelled as a transport problem from the centre of one region to the centre of a neighbouring region - with the maximum transmissible amount of electricity being restricted by the installed net transfer capacity (NTC). The transmission of electricity between model regions is associated with losses. Network constraints and transmission losses within a region are not explicitly modelled in LIMES-EU ('copperplate' assumption).

Storage Technologies Demand and supply of electricity have to be balanced in every time slice. Storage technologies may serve as an additional consumer in times of oversupply of electricity from generation technologies and as an additional producer of electricity in times of undersupply. The shift of electricity provision from one time slice to another is subject to storage losses. Three different storage technologies are available in LIMES-EU: pumped storage power plants (PSP), batteries, hydrogen electrolysis. The former two are assumed to do only *intra*day arbitrage and hydrogen electrolysis is allowed to do also *inter*day arbitrage. While *intra*day storages can only shift electricity provision between time slices of the same day, *inter*day storages are able to shift electricity provision between all-time slices of the same year. Furthermore, hydrogen electrolysis is assumed to only transform power into hydrogen and store it. Hydrogen is then used by one of the hydrogen-based generation technologies.

Carbon removals Given the very high abatement costs for some sectors, methods or systems aimed at removing carbon dioxide (CO_2) from the atmosphere might be necessary to balance residual emissions. Their role is increasingly seen as complementary to emissions reductions in pathways toward net-zero and climate neutrality goals. There are overall nature and technology approaches, the former offering rather temporary removals, e.g., afforestation, while the latter refers rather to permanent removals. In the model we consider two main technologies: bioenergy with carbon capture and storage (BECCS) in the electricity sector and direct air carbon capture and storage (DACCS). The former is considered within the generation technologies, while the latter plays only the role of a removal technology. Among DACCS, we include three technologies, namely liquid solvent, solid sorbent, and CaO ambient weathering[7].

Industry Technologies We consider four steelmaking production routes— Blast Furnace-Basic Oxygen Furnace (BF-BOF), Electric Arc Furnace (EAF), gas-based Direct Reduced Iron (NG-DRI-EAF), and hydrogen-based Direct Reduced Iron with EAF (H2-DRI-EAF)—each with specific requirements for fossil fuels, electricity, scrap, and hydrogen. Other alternatives such as Electrowinning and BF with top gas recycling + CCS (fossil) are not at a commercial stage yet, and thus are not considered[8].

3. Time Slice Approach

Long-term models with endogenous investments are computationally demanding, especially when optimizing intertemporally, i.e., optimizing investment decisions for multiple time steps simultaneously. A common way to reduce temporal complexity is to optimize dispatch decisions only for a limited number of representative time slices instead of modelling every hour of the year. However, it is not obvious which time slices should be selected from historic data in order to preserve the characteristic variability of electricity demand and vRES infeed. Consequently, Golling (2012), Nagl *et al.* (2013), de Sisternes Jimenez and Webster (2013), Poncelet *et al.* (2017) and others developed new approaches for selecting characteristic vRES infeed and demand pattern. However, none of those are satisfyingly applicable to the present

[7] We consider the most advanced DAC technologies only, all of them with at least one commercial plant available. However, there currently exist more than ten distinct systems at various stages of technological readiness (Küng et al., 2023).
[8] According to Diesing et al. (2025), the former has a TLR of 2-6, raises some sustainability concerns (depends on limited materials such as lithium, cobalt, neodymium and dysprosium), and its market entry is not expected before 2040. The latter appears frequently in the literature and has a TRL ranging from 6 to 9.

model as they either focus on only one RES technology or disregard different spatial compositions of load levels, which is pivotal in a multi-regional model.

Nahmmacher *et al.* (2016) develops a reproducible algorithm that is applied for LIMES-EU. It is used to select representative days with a given number of eight diurnal time slices; however, it can also be applied for selecting separate representative time slices or other groups of consecutive time slices. Due to its generic design, our method applies to all kinds of power system models with multiple fluctuating time series, i.e. models with multiple vRES technologies and/or multiple regions. The algorithm is meant to optimally fulfil three essential requirements, namely that the derived time slices should sufficiently reflect:

- the annual electricity demand and average vRES capacity factors for each region,
- the load duration curve of each time series, and
- the spatial and temporal correlation of electricity demand and vRES infeed.

The first requirement ensures that the quality of a region concerning solar and wind power is correctly reflected. By replicating both common and rare situations of load and vRES infeed as well as their respective frequency of occurrence (second requirement), the time slices neither overestimate nor underestimate single events. This serves to correctly value both base and peak load plants. The third requirement ensures that the characteristics of an interconnected multi-regional electricity system are correctly assessed and features such as large-area pooling and geographic smoothing are considered.

Our approach is based on Ward (1963)'s hierarchical clustering algorithm. We apply this algorithm on historic electricity demand and weather data to group days with similar diurnal demand and vRES infeed patterns. As a result, each group of days is reflected by a representative day in the power system model.

3.1. Data

We use ENTSO-E (2011) data for the historic electricity demand levels and historic weather data from the ERA-Interim dataset (Dee et al., 2011) for the vRES infeed. Using weather data rather than historic infeed data allows for taking into consideration a longer time span which prevents the overestimation of unusual years. The ERA-Interim dataset (Dee et al., 2011) comprises 33 years of ground solar irradiance and wind speed levels at 120m height for Europe. For every third hour between 1979 and 2011 the respective information is given for local data points in a spatial resolution of 0.75° × 0.75°. The conversion from weather data to vRES capacity factors is subject to the technology-specific power curves given in Section 4.1.

The three-hourly infeed of vRES technologies is averaged over all weather data grid cells belonging to the same region-specific resource grade. A comparison with real historic onshore wind feed-in levels however shows that realized capacity factors in mountainous countries[9] are much higher than the ones derived from the weather data. The spatial resolution of 0.75° × 0.75° is obviously not high enough to reflect the variations in wind speeds between mountain valleys and ridges. As wind turbines are predominantly installed on ridges rather than in valleys we adjust the wind data in the following way:

$$\{v_{adj}\} = \{v_{era}\} + 0.01\left(\{h_{q3}\} - \{h_{mean}\}\right) \tag{2}$$

$$\text{with } [v] = m/s,\ [h] = m$$

It is assumed that the representative elevation h_{q3} of wind sites equals the third quartile of the elevation distribution within a weather data grid cell[10]. It is further assumed that the increase in local wind speed $(v_{adj} - v_{era})$ at a point within a grid cell is in direct proportion to the difference in elevation of this point to the average elevation h_{mean} of the grid cell. The increase

[9] Spain in particular but also Austria and Italy.
[10] the distribution of elevation within a grid cell is based on NGDC (2013).

of 0.01 $\frac{m/s}{m}$ is chosen in order to best reflect the infeed levels of wind power observed in 2010 and 2011 (derived from Eurostat (2013a) and Eurostat (2013b)).

Country-specific demand data is retrieved from ENTSO-E (2011) in an hourly resolution. Compared to the vRES infeed, the intra-year demand fluctuations are less stochastic and follow distinct diurnal, intra-week and seasonal patterns. Though the absolute demand levels change between different years due to demographic and economic reasons, the relative intra-year fluctuations remain the same. The hourly demand data of 2010 and 2011 that is available for all model regions is therefore assumed to be representative for the *intra*-year demand side fluctuations between 1979 and 2011. Future *inter*-year growth of annual demand is subject to scenario assumptions (see Sections 4.2.1 and 8).

3.2. Clustering Approach

We apply an approach based on the hierarchical clustering algorithm described by Ward (1963) to select a limited number of characteristic days from the total of 12053 days between 1979 and 2011 for which the weather data is available (Dee et al., 2011). The approach ultimately yields a set of representative days that minimizes the sum of squared errors between all observed days and their representatives. By employing a multidimensional clustering algorithm, the approximation of any load duration curve of a region's electricity demand or vRES infeed is optimized while at the same time accounting for the simultaneous load and vRES levels of the other model regions.

The distance between two days (observations) is defined as the Euclidean distance respecting a total of 3016 dimensions[11] per observation. Before starting the clustering algorithm all-time

[11] Each observation contains data about 29 regions, 4 technologies, 3 resource grades per technology and region as well as region-specific demand data; each for every third hour of the day.

series are normalized to their maximum value. Subsequently, the algorithm iteratively groups similar days together until only one cluster containing all days remains. In each step, the clustering is done in a way that minimizes the variance within each cluster. Figure 2 visualizes the clustering procedure of our data.

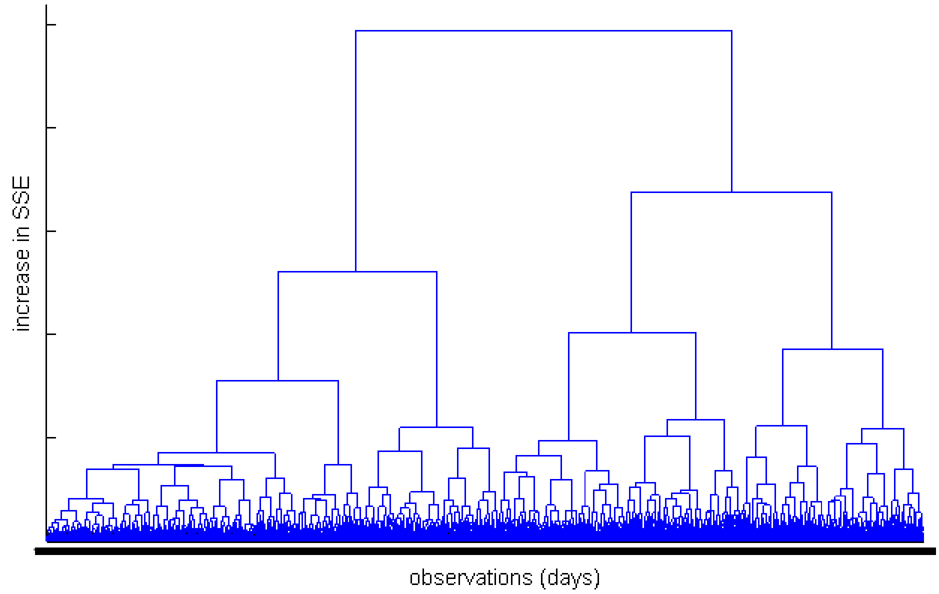


Figure 2. Dendrogram of clustering procedure. Showing the consecutive grouping of two clusters to a joint cluster and the resulting increase in the overall sum of squared errors (SSE, y-axis). All days (x-axis) are consecutively grouped together until only one cluster is left. Source: Own computation with model-specific data.

3.3. Resulting Time Slices

Once the clustering algorithm is finished, the model operator is free to choose the number of clusters to use for the model and thereby trade off temporal resolution against computation time. For each cluster, there is one representative day in the model. We choose that day as the representative day that is closest to the cluster's mean vector. In the model, a weighting factor is assigned to every representative day according to the number of days within its cluster. To ensure correct average demand levels and capacity factors per technology and region the time series are scaled if necessary.

Nahmmacher *et al.* (2016) analyse the differences in model results depending on the number of time slices. They show that already 48 time slices, i.e., 6 representative days, are sufficient to reflect the characteristic fluctuations of electricity demand and vRES infeed in LIMES-EU. Further model tests show that emissions are very similar for runs with 6 or more days.

4. Power sector

This section elaborates on the power sector representation, going through the main technology characteristics and region-specific parametrisation such as electricity demand, installed capacities and resource potentials.

4.1. Technology Characteristics

This section provides details on the techno-economic characteristics of the different technologies included in the model. All monetary values in this document are expressed in real EUR2010, adjusted for inflation where applicable. For simplicity and readability, we use 'EUR' throughout the text to denote these values.

4.1.1. Generation Technologies

Intermittent Generation Technologies

Intermittent technologies comprise the generation technologies that are based on wind and solar power. For wind power LIMES-EU discerns between onshore and offshore power plants. Solar power technologies are divided into PV cells and CSP plants. Table 1 and Table 2 give the techno-economic characteristics of these power plants. As the future development of their investment costs is highly uncertain, it is usually subject to a sensitivity analysis.

Table 1. Default assumptions for vRES investment costs (€/kW). Investment costs after 2050 are assumed to remain constant at the 2050 value.

	Wind Onshore	Wind Offshore	PV	CSP
2020	1179	2336	474	3281
2025	1039	2079	420	2879
2030	898	1821	366	2476
2035	863	1673	332	2400
2040	828	1524	299	2324
2045	816	1482	281	2272
2050-2070	805	1441	263	2220

Source: European Commission (2024) and own assumptions.

The output of intermittent generation technologies is constrained by the region- and time-slice-specific availability and subject to technology-specific power curves. Power curves describe the relation between resource availability (wind speed or solar irradiance) and possible electricity production of a respective power plant.

Table 2. Characteristics of wind and solar power plants.

	Fixed O&M (%/a)	Lifetime (a)
Wind Onshore	2	30
Wind Offshore	2	30
PV	3	30
CSP	4	25

Source: European Commission (2021a).

Turbine-specific wind power curves are published by the respective turbine producers. However, using power curves of commonly installed wind turbines to derive capacity factors from the weather data yields much higher values compared to historically realized full load hours (see Boccard (2009) for possible reasons). We therefore use the following regression to derive an aggregated wind power curve for the model (Equation (3)). It is based on 2011-data of hourly German wind power production P_{Wind} (ÜNB, 2013a) and installed capacities[12] cap_i (ÜNB, 2013b) as well as the ERA-Interim wind speed data v_i (Dee et al., 2011) per weather data grid cell i. It is assumed that the power output is proportional to the fifth power of the wind speed[13]. The resulting wind power curve which is defined by the five coefficients β_{1-5} is depicted in Figure 3.

$$P_{Wind} = \sum_i cap_i\left(\beta_1 v_i + \beta_2 v_i^2 + \beta_3 v_i^3 + \beta_4 v_i^4 + \beta_5 v_i^5\right) \tag{3}$$

The output of PV cells is assumed to be in a linear relation to the solar irradiance. In contrast to PV cells that use both direct and diffuse irradiance, CSP plants can only produce electricity from direct solar irradiance. Following Haller *et al.* (2012), the direct solar irradiance is derived from a simplified approximation which assumes that the direct normal irradiance DNI_i is a function of the global solar irradiance I_i and the latitude lat_i of the weather data grid cell i (Equation (4). This way the DNI share of global irradiance is 75% at a latitude of 30° and decreases for larger latitudes.

$$DNI_i = I_i\left(1 - 0.25\left(\frac{lat_i}{30}\right)^{1.6}\right) \tag{4}$$

[12] The plant-specific installed capacities are aggregated according to the weather data grid.

[13] The power P of a free-flowing wind stream is given by $P = \frac{1}{2}v^2\dot{m} = \frac{1}{2}v^2(vA\rho)$, with $\dot{m}$ denoting the mass flow rate, v the wind speed, ρ the air density and A the flow cross-section. Hence the power *input* of a wind turbine is proportional to the third power of the wind speed. The power *output* is nonetheless subject to a wind speed dependent power coefficient which is accounted for by also including the 4th and 5th power of v.

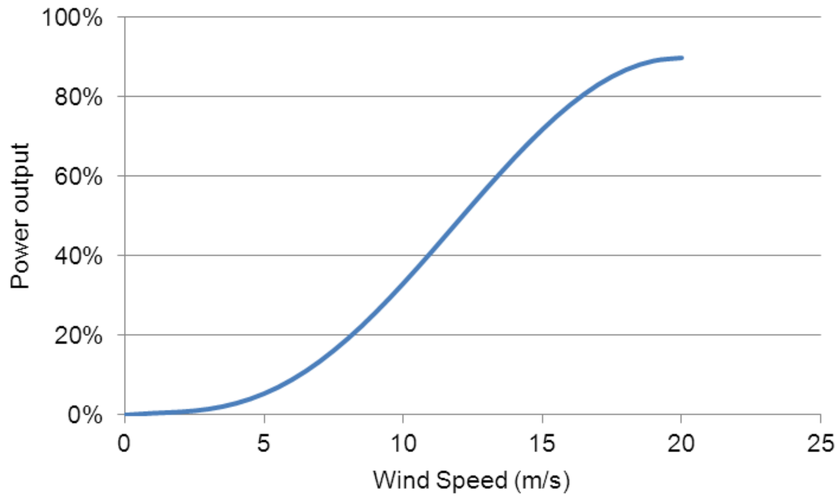


Figure 3. Aggregated wind power curve. Source: Own calculations based on Dee et al. (2011), ÜNB (2013a) and ÜNB (2013b).

As in Haller *et al.* (2012), CSP plants are modelled with a collector area that is four times the size required to reach nominal output at reference conditions (SM4[14] configuration). Each CSP plant is equipped with internal thermal storage with a capacity large enough to level out the diurnal fluctuations in solar energy input. Thus, even though solar irradiance varies between time slices, CSP plants are dispatchable within the limits of their daily availability factors that differ across days.

Dispatchable Generation Technologies

Power plants using fossil fuels, uranium, biomass or hydropower as a primary energy source are dispatchable within the limits of their annual availability. Except for hydro[15], the annual availability does not depend on the region. Hourly availability for all technologies is defined as 100%. Table 3 gives an overview of the techno-economic characteristics of thermal- and hydro-based power plants in LIMES-EU.

[14] SM: solar multiple.
[15] See Section 0.

Table 3. Techno-economic characteristics of thermal and hydropower plants. When efficiency ranges are given, they refer to plants installed from 1970 to 2015, with plants installed after 2010 having the value at the upper end of the range.

	Lifetime (yr)	Investment costs (EUR/kW)	Efficiency (%)	Annual availability (%)	Auto-consumption (%)	Fixed O&M (%CAPEX/yr)	Variable O&M (EUR/MWh)	Min Load (%)	Max Ramp (%)
Nuclear	60	6000	38	80	5	2	6	40	-
Hard Coal	40	1650	38-45	75-78	7	3	4	25-40	35
Hard Coal CCS	40	see Table 4	36	78	24	2	5	25	35
Lignite	40	1800	36-41	75-78	10	3	4	25-50	25
Lignite CCS	40	see Table 4	32	78	25	3	6	50	25
Gas CC	30	see Table 4	54-60	77-80	3	4	2	40-50	50
Gas CC CCS	30	see Table 4	43	80	16	2	3	40	50
Gas GT	25	see Table 4	35	78	1	3	2	40	100
Oil	25	see Table 4	39	75	5	3	2	50	100
Hydrogen CC	30	see Table 4	57	80	2	3	4	40	50
Hydrogen CT	25	see Table 4	33	78	1	4	3	20	100
Hydrogen FC	20	see Table 4	68	28	0	2	1	70	12
Waste	40	2000	18	78	2	4	3	25	100
Other gases	40	900	76	78	8	3	3	40	100
Biomass	40	see Table 4	40	78	10	2	4	25	38
BECCS	40	see Table 4	42	78	27	2	6	25	35
Hydro	55	1908	100	Depending on region	2	2	0	0	100

Source: European Commission (2024), Danish Energy Agency (2025), ENTSO-E (2020); own assumptions.

Table 4. Default assumptions for dispatchable technologies with time-dependent investment costs (EUR/kW). Investment costs after 2050 are assumed to remain constant at the 2050 value.

	2020	2025	2030	2035	2040	2045	2050-2070
Hard Coal CCS	3145	3029	2913	2793	2673	2654	2636
Lignite CCS	3515	3399	3283	3237	3191	3145	3098
Gas CC	555	545	536	533	531	529	527
Gas CC CCS	2039	1942	1844	1722	1600	1552	1505
Gas GT	370	363	357	356	354	353	351
Oil	353	343	334	329	325	320	315
Hydrogen CC	583	572	563	560	558	555	553
Hydrogen CT	389	381	375	374	372	371	369
Hydrogen FC	3237	3048	2858	2757	2656	2562	2468
Biomass	1850	1757	1665	1619	1572	1572	1572
BECCS	3746	3572	3399	3228	3057	3011	2964

Source: European Commission (2024), Danish Energy Agency (2025);own assumptions.

Power plants with steam turbines are subject to minimum load restrictions and ramping constraints. Applying these constraints to the entire plant fleet would not be accurate because not all installed capacity is necessarily available at every point in time. To represent these characteristics, the dispatch is limited via two equations: first, the model computes the maximum capacity that is operating during a representative day. Then, it can reduce the generation in each time slice of that day down to the minimum load times the operating capacity, as long as the variation between two time steps is within the ramping limit. The minimum load and maximum ramping restrictions are given in Table 3 as the share of the operating capacity within a day. Efficiency losses due to part load operation are disregarded. We furthermore limit the flexibility of nuclear such that the operating capacity has to be the same for each representative day within one year.

The prices for primary energy sources used in thermal power plants are exogenous to LIMES-EU and thus independent from demand[16] (see Table 5); as part of the calibration process we add cost mark-ups for lignite, gas and hard coal for certain model regions. Waste and other gases prices are considered negligible and assumed at 0.1 EUR/GJ to avoid computational problems in the model.

Table 5. Fuel prices. Except for biomass, we assume they remain constant after 2050.

	Fuel prices (€/GJ)										
	2020	2025	2030	2035	2040	2045	2050	2055	2060	2065	2070
Hard Coal	1.2	1.8	2.4	2.6	2.7	2.9	3.0	3.0	3.0	3.0	3.0
Lignite	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Natural Gas	3.0	9.1	5.3	6.0	6.8	7.6	7.6	7.6	7.6	7.6	7.6
Uranium	0.7	0.8	1.0	1.2	1.4	1.7	2.0	2.0	2.0	2.0	2.0
Biomass	6.0	6.0	6.0	8.0	12.0	16.0	20.0	23.0	25.0	26.0	28.0
Oil	5.3	8.3	10.9	12.4	13.2	14.4	15.9	15.9	15.9	15.9	15.9
Waste	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
Hydrogen	50.8	42.1	24.5	22.3	20.2	18.0	15.8	15.8	15.8	15.8	15.8
Other gases	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1

Source: European Commission (2024), Umwelt Bundesamt (2022), REMIND[17] , Strefler et al. (2021); own assumptions.

Power generation from hard coal, lignite, natural gas, oil, waste and other gases emits greenhouse gases; the CO_2 intensity of these primary energy sources is given in Table 6 as well. The stated emission factors are estimated from IPCC Guidelines (Gomez et al., 2006) and are considered equal for every model region. We estimate waste and other gases emissions from

[16] i.e. all model regions are assumed to be price takers on the fuel markets.

[17] For REMIND detailed harmonized model documentation is available at the Common IAM documentation, https://www.iamcdocumentation.eu/Model_Documentation_-_REMIND

BMWi (2018), and assume those values across countries for simplicity and due to the lack of sufficient data.

Table 6. Emission factors.

	CO_2 intensity	
	tCO_2/TJ	gCO_2/kWh_{th}
Hard Coal	96	347
Lignite	107	387
Natural Gas	56	200
Biomass	100	360
Oil	81	290
Waste	154	554
Other gases	203	730

Source: Gomez et al. (2006) and BMWi (2018); own assumptions.

The only generation technology considered able to provide negative emissions is biomass coupled with CCS. Owing to carbon emissions associated with the initial land use change and these subsequent emissions, the actual amount of emissions removed depends entirely on the choices made throughout the supply chain. According to Fajardy and Dowell (2017), carbon intensity would vary as much as ~-1100 to 1000 gCO_2/kWh for short rotation cropping willow as the offset effect is exacerbated with indirect land use changes. The supply chain emissions cannot be entirely accounted for because some of these emissions are already covered by the EU ETS or ESR (e.g., transport of biomass, included in the ESR). However, unlike other primary energies, harvesting biomass directly affects the absorption of CO_2, and thus the countries' emission inventories. Hence, land use change (LUC) and indirect land use change (ILUC) should be accounted. Based on carbon content of 100 tCO_2/TJ for biomass (Gomez et al., 2006), and assuming a capture rate of 90%, efficiency of 29% and an offset factor of 50%[18],

[18] Different estimations about the negative emissions potential are found in literature. For instance, Fajardy and Dowell (2017) estimate this between 46% and 62% of the carbon intensity, depending on whether LUC and ILUC are accounted. Heck et al. (2018) estimate also negative emissions potentials accounting for ~50% of the total captured by BECCS.

the emission factor for BECCS would be -551 gCO_2/ kWh_{el}. Further research is required to estimate more accurately to what extent negative emissions from BECCS are offset.

4.1.2. Storage Technologies

The purpose of storage technologies is to ease the match between supply and demand over time. In LIMES-EU we consider three storage technologies: pumped storage power plants (PSP) and batteries for balancing between time slices of the same day (*intra*day storage), and hydrogen electrolysis for balancing between time slices of the same year (*inter*day storage). The technical and economic features of the three storage options are given in Table 7 and Table 8. We do not account for possible regional expansion constraints, e.g., suitable sites for pumped-hydro storage systems, regarding these specific storage technologies. Still, PSP investments are usually limited in the model.

Finally, unlike PSP and batteries we assume that hydrogen electrolysis facilities do not have a generation unit, i.e., they cannot generate electricity from the hydrogen produced. The stored hydrogen can only be used by any of the three hydrogen-based generation technologies (see Table 3 and Table 4 above) considered. Therefore, hydrogen electrolysis parameters in Table 7 and Table 8 only reflect the power-to-hydrogen unit. This means that electrolysis efficiency is not the roundtrip value, but rather just the conversion efficiency of electricity into hydrogen.

Given the lack of maturity of electrolysis, the magnitude of future costs is highly uncertain and estimations vary widely, from as low as 0.02 €/kWh for below-ground storage (Steward et al., 2009) to as much as 31 €/kWh (Schmidt et al., 2019), without specifying on the storage tank technology. Indeed, above-ground storage appears to have significantly higher investment costs, e.g., 20 €/kWh reported by Steward et al. (2009). Reuß et al. (2017) suggest that below-ground storage is the most promising alternative for hydrogen on a large scale. They assume ~10 €/kg for pressurized tank and ~1 €/kg for liquefied H_2 tanks, while calculating <1 €/kg for cavernous storage. This translates into <0.03€/kWh for cavernous storage. We thus assume mostly cavernous gas storage with the addition of some local tanks to buffer peaks on the H_2 network (similarly to the gas network), which would translate into ~0.1 €/kWh for hydrogen storage.

Table 7. Characteristics of storage technologies.

	Power Inv. Costs (€/kW)	Storage Inv. Costs (€/kWh)	Fixed O&M (%/a)	Variable O&M (€/MWh)	Efficiency (%)	Lifetime (yr)
Pumped storage	938	66	1	0	78	80
Batteries	see Table 8	see Table 8	1	0	80	20
Hydrogen electrolysis	see Table 8	see Table 8	2	3	70	20

Source: Schmidt et al. (2019) and own assumptions.

Table 8. Storage technologies with time-dependent investment costs. Investment costs after 2050 are assumed to remain constant at the 2050 value.

Technology	Type of cost	2010	2015	2020	2025	2030	2035	2040	2045	2050-2070
Batteries	Power (€/kW)	563	563	310	191	130	101	90	84	79
	Storage (€/kWh)	666	666	366	227	153	120	107	100	93
Hydrogen Electrolysis	Power (€/kW)	2521	2521	2521	1576	882	819	756	693	630
	Storage (€/kWh)	2.8	2.8	2.8	2.3	1.9	1.6	1.4	1.3	1.1

Source: Schmidt et al. (2019), Danish Energy Agency (2025), Ramboll (2023) and own assumptions.

The representative days are not modelled in a fixed order as they might cluster days from different months and thus it is not possible to determine a chronological order. As a result, we cannot accurately model seasonal storage and the corresponding investment needs of electrolysis. Instead, we implement a proxy for electrolysis storage capacity (hydrogen storage capacity). We assume an exogenous number of cycles, which is defined as the ratio between storage capacity and hydrogen demand (i.e., output from electrolysis). We also assume that a minimum share of the hydrogen consumed either for electricity generation or in other sectors (exogenous) should be produced by electrolysis. The remaining is assumed to be imported by the EU at the prices shown in Table 5. The default assumption is that hydrogen is supplied entirely by electrolysis within the modelled countries (i.e., endogenous in the model), i.e., hydrogen imports are not allowed.

4.1.3. Transmission Technologies

Transmission expansion between countries is modelled endogenously in LIMES-EU. For enabling the joint optimization of generation, storage and transmission expansion within one model run the transmission grid is represented by 'net transfer capacities' (NTC). The NTC approach abstracts from the complex power flows of the highly intermeshed European transmission network by stating a simple transport problem for the electricity exchange between two neighbouring countries. The installed NTC between two countries defines the maximum tradable power flow within a given time slice and remains constant throughout the year. Higher power flows are possible after investing in transmission expansion thereby increasing the NTC between the two countries. Investment costs depend on the additional capacity to be installed and the distance between the two country centres. The costs, based on Carlsson et al. (2014), are adjusted as they assume a discount rate of 8%. These correspond to overhead transmission infrastructure costs that apply to 500 MVA installations. Table 9 and Table 10 summarise the main techno-economic parameters of cross-border transmission.

Table 9. Technical parameters of cross-border transmission.

Availability (%)	Lifetime (yr)	Losses (%/1000km)
80	60	7

Source: Carlsson et al. (2014); own assumptions.

Table 10. Investment costs in cross-border transmission (EUR/km-KW).

2020	2025	2030	2035	2040	2045	2050-2070
1.1	1.0	0.9	0.9	0.9	0.9	0.8

Source: European Commission (2021a); own assumptions.

4.1.4. Depreciation of installed capacities

All technologies in LIMES-EU are characterized by technology-specific lifetimes. However, even before reaching their maximum lifetime, installed capacities are subject to degradation. This is implemented via the depreciation factor $\omega_{\tilde{t},te}$ which depends on the lifetime ψ_{te} of a technology *te* and the time $\tilde{t}$ that has passed since its installation (Equation (5)). Only the share $\omega_{\tilde{t},te}$ of the installed capacity can be used for electricity generation, storage or transmission, respectively. Figure 4 visualizes the depreciation factor $\omega_{\tilde{t},te}$ for three different technological lifetimes: 20, 40 and 60 years.

$$\omega_{\tilde{t},te} = 1 - \left(\frac{\tilde{t}}{\psi_{te}}\right)^6 \qquad \forall te, \tilde{t} \leq \psi_{te} \tag{5}$$

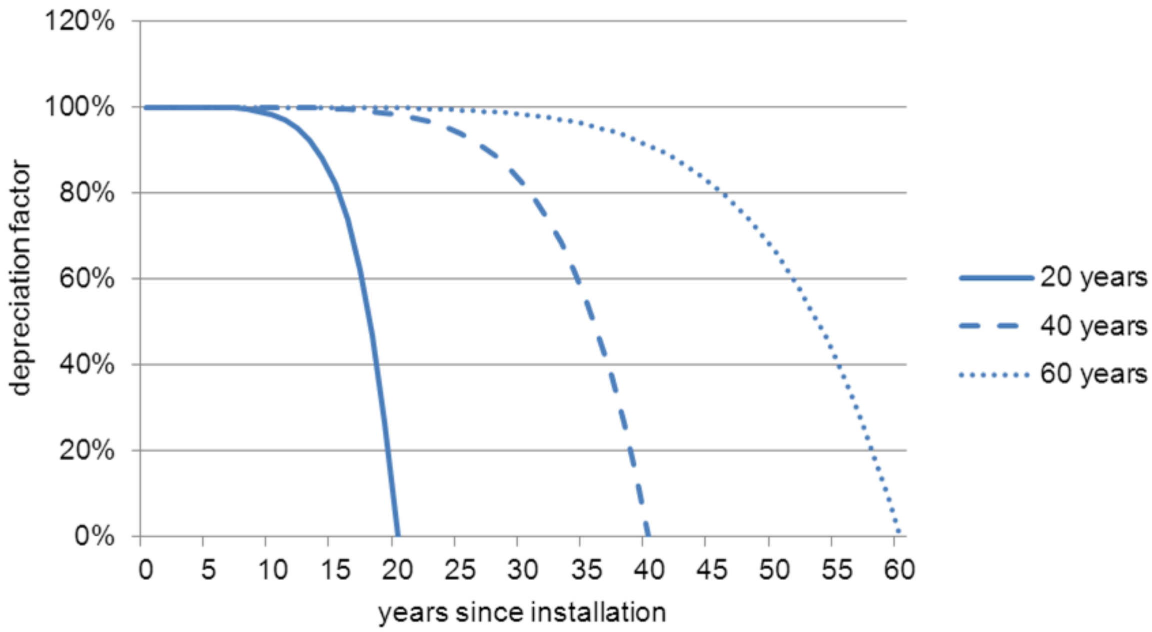


Figure 4. Depreciation factor ω for three different technological lifetimes (20, 40, 60 years).

4.1.5. Security of supply and reserves

Besides the operating constraints considered for dispatchable technologies (minimum load and ramping constraints), we assume that countries implement measures to ensure secure power system operation by having sufficient overcapacity for an emergency. A 15% capacity margin is considered, i.e., firm capacity (after applying derating factors) and reserves have to exceed demand by at least 15% at any time. Although the capacity requirements are considered for all the time slices, these are normally only binding at peak hours. Table 11 shows the assumed derating factors and the variables that they multiply to estimate the de-rated capacity. While de-rated capacity of dispatchable technologies is computed on the hourly capacity available, the de-rated capacity of intermittent technologies (i.e., variable renewables) is computed on their maximum output using a substantially lower derating factor (with respect to dispatchable technologies) to account for their lower reliability. The maximum output already depends on vRES availability factors, and thus accounts for hourly and seasonal patterns. For storage we de-rate output to avoid overestimating the adequacy contribution of these technologies, and only 70% of net imports are considered. The detailed calculations are presented in Appendix A.g.

Table 11. Derating factors.

Type of technology	Derating factor	Variable derated
Dispatchable technologies	0.93	Installed capacity*Hour availability
Intermittent technologies	0.25	Max. availability
Storage technologies	0.5	Output
Net imports	0.7	Volume

Source: Own assumptions.

4.2. Region-Specific Input Data

4.2.1. Electricity Demand

Annual demand

As discussed in Section 3, electricity demand is not entirely exogenous in the model. Certain technologies such as electrolysers and DACCS consume electricity and their operation depend on market conditions. In this section, we focus on the part of the demand that is exogenous and the different assumptions for its long-term estimation. This component of demand is overall the lion share of electricity consumption as this corresponds to all economy sectors.

We depart from the electricity demand in the EU Reference scenario 2020 (European Commission et al., 2021) for EU27. For other countries we use national sources, namely BEIS (2021) for UK and DNV (2021) for Norway; for the Balkan region we derive demand scaling historical consumption by the growth rates of its neighbouring countries. Since the projections of electricity consumption in the transport sector are rather conservative and the transport sector might have very different load profiles compared to the historic ones, we decompose electricity demand into consumption for the transport sector and the rest. We use the projected electricity demand in the transport sector from the EU Reference scenario 2020 (European Commission et al., 2021) and scale it based on EU-wide data. For the period 2025-2030, we use data from the "Fit for 55' MIX-CP scenario (European Commission, 2021b) and for 2050 from the Impact Assessment (European Commission, 2020). We scale UK transport electricity consumption also with a high demand scenario from BEIS (2021). For years after 2050 until 2070, we assume that the demand is fixed at 2050 values.

Based on historical data, it is assumed that the required electricity production has to exceed the reported final electricity consumption by 8% to account for intra-regional transmission and distribution losses. Table 12 reports the resulting exogenous component of electricity demand. An explanation of the region codes used in this document is given in Appendix B.

Table 12. Default assumptions for final electricity demand (in TWh).

Region	2020	2025	2030	2035	2040	2045	2050-2070
BE	81	85	96	98	101	107	113
BG	30	30	31	32	32	34	36
CZ	59	57	61	65	69	74	79
DK	33	39	46	48	51	54	56
DE	490	494	533	566	592	644	693
EE	8	8	9	10	10	11	12
IE	29	33	42	46	49	53	56
GR	49	53	56	58	61	66	73
ES	227	233	245	258	269	289	308
FR	420	395	396	422	436	463	492
HR	16	17	17	18	19	20	22
IT	284	278	303	314	336	371	404
LV	7	7	8	8	9	9	10
LT	11	10	10	11	11	13	14
LU	6	6	7	7	8	8	9
HU	41	40	45	48	50	53	57
NL	114	122	129	136	140	152	166
AT	64	61	63	67	71	76	82
PL	148	149	164	176	187	204	222
PT	47	47	49	51	53	58	62
RO	48	54	62	66	67	71	75
SI	13	15	17	18	19	21	22
SK	25	27	28	30	31	33	35

Region	2020	2025	2030	2035	2040	2045	2050-2070
FI	78	83	91	93	98	102	106
SE	126	120	126	131	135	142	149
GB	288	287	333	421	458	504	550
NO	122	160	177	186	192	194	191
CH	63	63	64	67	71	75	76
Balkan	55	58	64	66	68	70	73

Source: BEIS (2021), DNV (2021), European Commission (2021b, 2020), European Commission et al. (2021); own assumptions.

Hourly patterns

As explained in Section 3.2, we use a clustering algorithm to derive the hourly demand. These nonetheless follow the patterns from 2010-2011 load data (ENTSO-E, 2011). Because penetration of electric vehicles was marginal then, we use the resulting load profile to estimate the hourly demand for the non-transport component. Having a differentiated hourly profile for the transport sector allows us to capture potential changes in demand patterns due to a higher share of electricity consumption in the transport sector.

For the transport demand component, we use data from Heinz (2018). We aggregate charging load from the different day types (i.e., weekday and weekend) and charging location (i.e., residence, workplace and public spaces). Although this study is focused on Germany, given the lack of data for other countries, we assume the same charging behaviour across countries. The resulting electricity demand profile from the transport sector (as a factor multiplying average hourly demand) is shown in Figure 5.

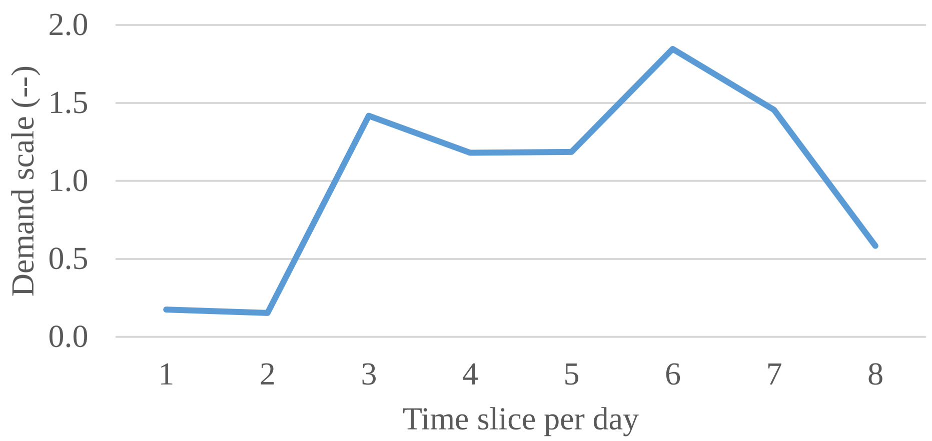


Figure 5. Electricity demand profile from the transport sector (as a factor multiplying average hourly demand) per time slice. Source: Heinz (2018); own assumptions.

Besides potential changes in future hourly consumption patterns, there has been substantial changes in some countries' peak demand between 2010 and 2020 (recall that overall hourly profiles are computed based on 2010-2011 data). For instance, peak demand in GB decreased from 61 GW in 2010 to (expectedly) 48 GW in 2020 (ENTSO-E, 2019) (see Table 13), i.e., 21%. In the same period, annual demand only decreased from 329 to 325 TWh (i.e., 1%). Hence, we rescale overall hourly profiles as of 2020 using the peak demand for the winter 2019/2020 ($peakdem_{t,r}$). Our rescaling methodology ensures that the variability of the clustered demand remains unchanged.

Table 13. Peak demand in 2010 and 2020.

Region	2010	2020	Region	2010	2020	Region	2010	2020
FI	14.6	13.4	NL	18.1	18.2	HU	5.6	6.3
NO	20.7	21.9	PL	19.5	25.1	RO	6.8	9.3
SE	24.8	26.7	DE	84.7	79.9	SI	1.9	2.4
EE	1.3	1.4	BE	14.0	13.2	FR	88.6	82.2
LV	1.1	1.2	LU	1.0	1.0	HR	2.8	2.9
LT	1.4	2.1	CZ	9.6	10.6	BG	4.9	6.3
DK	6.0	6.0	SK	3.9	4.6	IT	51.9	51.6
GB	60.6	48.1	AT	10.1	11.5	ES	38.9	39.5
IE	4.5	5.3	CH	9.7	10.3	PT	8.8	7.3

Region	2010	2020
GR	8.8	8.0

Region	2010	2020
Balkan	10.6	12.2

Source: ENTSO-E (2019, 2011); own assumptions

We assume that ‘capacity factor’ (cf_r) of peak demand is constant for every country.

$$cf_r = \left(\sum_\tau d_{2020,\tau,r} \Big/ peakdem_{2020,r} \right) (1/8760) \tag{6}$$

We calculate the variability of the maximum clustered demand ($deltadem_r$) assuming the recalculated ‘capacity factor’.

$$deltadem_r = \left(\max_\tau d_{2020,\tau,r} * cf_r - \sum_\tau d_{2020,\tau,r} * (1/8760) \right) / (1 - cf_r) \tag{7}$$

We then aggregate such delta and the (original) clustered hourly demand

$$dem\_nonadj_{\tau,r} = d_{2020,\tau,r} + deltadem_r \tag{8}$$

We recalculate the demand scale ($demscale\_adj_{\tau,r}$), i.e., ratio between demand and average demand

$$demscale\_adj_{\tau,r} = dem\_nonadj_{\tau,r} * 8760 \Big/ \sum_\tau dem\_nonadj_{\tau,r} l_\tau \tag{9}$$

And use such demand scale to compute (again) the hourly demand as of 2020 ($d_{t,\tau,r}$)

$$d_{t,\tau,r} = demscale\_adj_{\tau,r} * \sum_\tau d_{2020,\tau,r} * (1/8760) \qquad \forall t \geq 2020 \tag{10}$$

4.2.2. Installed Capacities in 2025

Generation

Installed capacities are set exogenously for the period 2010 to 2025. Capacities from 2010 are taken from Platts (2011). Figure 6 shows the sources for capacities between 2015 and 2025, and Table 14 shows capacities in 2025. Since 2025 data is not available yet, we use capacities from 2024 to estimate this value. For RES --except for biomass-- and batteries, we assume the 2025 value corresponds to that in 2024 plus the annual increase between 2020 and 2024. For thermal and nuclear we assume the same value as in 2024. For technologies where there is missing data, we make different assumptions: for waste in EU27 in 2025, we assume that the change in capacity between 2020 and 2025 (positive or negative) equals to that between 2015 and 2020; for the remaining empty cells in Figure 6 we assume capacity is 0.

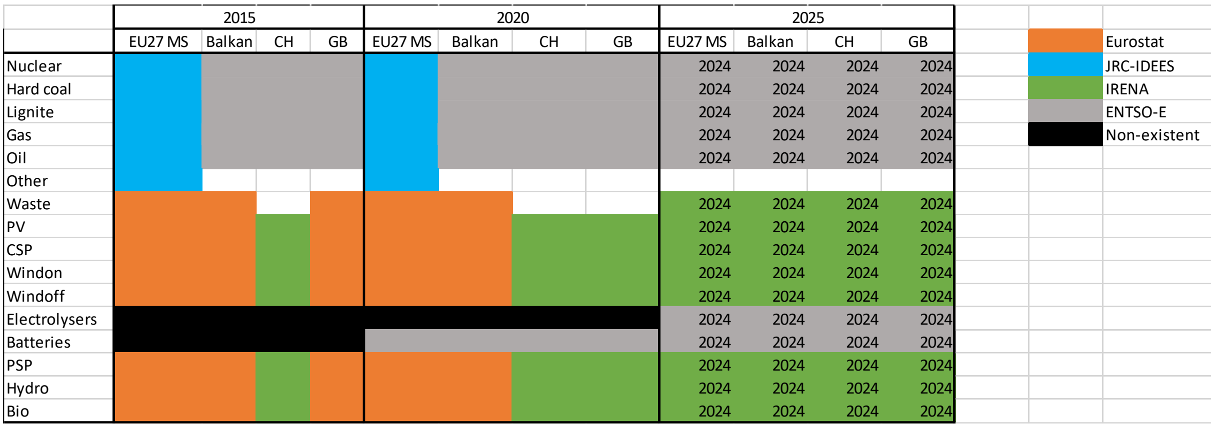


Figure 6. Sources for installed capacity. These are specifically: Eurostat (2025), IRENA (2025), Rozsai et al. (2024), and ENTSO-E (2024, 2021, 2015).

For hard coal, lignite and gas, we consider different vintages to capture improvements in efficiency over time. Additionally, we consider two types of technologies for gas-fired plants, namely combined cycle and gas turbines. We only consider vintages for the former. We let the model compute how the aggregate capacities are allocated among these vintages/individual technologies.

Table 14. Installed generation and storage power capacities in 2025 (in GW).

	Nuclear	Hard coal	Lignite	Gas	Oil	Waste	Biomass	Hydropower	PV	CSP	Wind onshore	Wind offshore	PSP
BE	3.9	0.0	0.0	5.6	0.1	0.3	0.7	0.1	10.8	0.0	3.5	2.4	1.3
BG	2.0	0.1	2.9	1.2	0.0	0.0	0.1	2.5	4.5	0.0	0.7	0.0	0.9
CZ	4.1	0.6	5.1	1.4	0.0	0.1	0.8	1.1	4.6	0.0	0.4	0.0	1.2
DK	0.0	2.5	0.0	2.0	1.0	0.4	1.8	0.0	4.7	0.0	4.9	3.0	0.0
DE	0.0	10.0	15.1	26.0	1.6	3.1	9.0	5.9	98.1	0.0	65.7	9.5	5.3
EE	0.0	0.0	0.0	0.0	1.3	0.2	0.2	0.0	1.6	0.0	0.6	0.0	0.0
IE	0.0	0.5	0.1	4.1	0.6	0.1	0.0	0.2	1.6	0.0	5.1	0.0	0.3
GR	0.0	0.0	2.7	6.0	0.7	0.0	0.2	3.4	10.6	0.0	5.7	0.0	0.0
ES	7.1	1.8	0.0	24.5	0.0	0.3	1.2	16.8	41.8	2.3	33.0	0.0	3.3
FR	63.0	1.7	0.0	7.2	1.3	1.0	2.9	24.7	23.7	0.0	24.4	1.8	2.3
HR	0.0	0.3	0.0	1.5	0.3	0.0	0.2	2.2	1.0	0.0	1.3	0.0	0.0
IT	0.0	4.7	0.0	41.5	0.9	0.8	3.0	19.0	39.0	0.0	13.4	0.0	4.0
LV	0.0	0.0	0.0	1.0	0.0	0.0	0.1	1.6	0.6	0.0	0.1	0.0	0.0
LT	0.0	0.0	0.0	1.2	0.0	0.1	0.1	0.1	3.1	0.0	2.1	0.0	0.8
LU	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.6	0.0	0.2	0.0	1.3
HU	1.9	0.2	0.6	2.2	0.5	0.1	0.6	0.1	9.0	0.0	0.3	0.0	0.0
NL	0.5	4.0	0.0	14.4	0.0	0.9	0.5	0.0	27.4	0.0	7.6	5.5	0.0

	Nuclear	Hard coal	Lignite	Gas	Oil	Waste	Biomass	Hydropower	PV	CSP	Wind onshore	Wind offshore	PSP
AT	0.0	0.0	0.0	3.7	0.1	0.9	1.0	15.2	9.8	0.0	4.2	0.0	0.0
PL	0.0	14.3	7.6	5.2	0.0	0.2	1.1	1.0	23.9	0.0	10.9	0.0	1.3
PT	0.0	0.0	0.0	3.8	0.0	0.1	0.7	8.6	6.8	0.0	5.6	0.0	0.0
RO	1.3	0.2	1.7	2.1	0.0	0.0	0.2	6.6	5.3	0.0	3.1	0.0	0.1
SI	0.7	0.1	0.8	0.6	0.0	0.0	0.1	1.2	1.5	0.0	0.0	0.0	0.2
SK	2.3	0.0	0.0	0.8	0.1	0.0	0.2	1.6	0.9	0.0	0.0	0.0	0.9
FI	4.4	2.2	0.0	1.5	0.0	0.2	3.0	3.2	1.4	0.0	9.6	0.0	0.0
SE	7.0	0.0	0.0	0.4	0.1	1.5	3.2	16.5	5.8	0.0	18.8	0.2	0.0
GB	6.7	0.0	0.0	36.5	0.4	0.0	6.8	2.2	18.5	0.0	16.6	15.7	2.6
NO	0.0	0.0	0.0	0.0	0.0	0.1	0.0	35.1	0.9	0.0	5.5	0.1	0.0
CH	2.9	0.0	0.0	0.0	0.0	0.0	0.0	16.5	8.9	0.0	0.1	0.0	0.6
Balkan	0.0	0.0	7.8	0.7	0.0	0.0	0.1	8.3	1.9	0.0	1.1	0.0	1.1

Source: IRENA (2025), and ENTSO-E (2024);own assumptions.

In light of the long construction time and planning process, and partly political decision, of nuclear power, we also include exogenously the capacity additions to take place between 2030 and 2045 if such plants have already started construction. For other countries, unless there is a moratorium or a nuclear phase-out has carried out, investments remain endogenous These are summarised in Table 15.

Table 15. Exogenous nuclear capacity additions. Source: World Nuclear Association (2025, 2024).

Country	**Capacity addition**	**Year**
GB	1.72	2030
GB	1.72	2035
BG	1.25	2035
BG	1.25	2040

Transmission

The cross-border transmission capacities correspond to the average value of NTC's in both directions for each of the existing and potential cross-border links. As for generation and storage, we fix capacities between 2010 and 2025. Table 16 shows values in 2025, based on the Reference grid from EMBER (2023). As the precise age structure of the transmission network is unknown, we assume that the existing lines in 2010 were either constructed or refurbished after 1985 and that investments into the grid were equally distributed between 1985 and 2010 (relevant for the obsolescence of transmission capacities).

Table 16. Transmission capacities in 2025 between model regions (GW).

Link	Capacity	Link	Capacity	Link	Capacity
AT-CH	1.20	AT-IT	0.80	BE-DK	0.00
AT-CZ	0.90	AT-SI	0.95	BE-FR	4.30
AT-DE	5.40	AT-SK	0.00	BE-GB	0.00
AT-HU	0.80	BE-DE	1.00	BE-LU	0.68

Link	Capacity	Link	Capacity	Link	Capacity
BE-NL	3.40	DE-NL	5.00	FR-LU	0.38
BG-GR	1.70	DE-NO	1.40	GB-IE	0.00
BG-RO	1.50	DE-PL	3.00	GB-NL	0.00
Balkan-BG	0.82	DE-SE	0.62	GB-NO	0.00
Balkan-GR	1.50	DK-GB	0.00	GR-IT	0.50
Balkan-HR	1.25	DK-NL	0.70	HR-HU	1.70
Balkan-HU	0.75	DK-NO	1.64	HR-SI	2.00
Balkan-IT	0.60	DK-PL	0.00	HU-RO	1.10
Balkan-RO	0.68	DK-SE	2.45	HU-SI	1.20
CH-DE	4.20	EE-FI	1.02	HU-SK	2.60
CH-FR	3.70	EE-LV	1.10	IT-SI	0.66
CH-IT	3.75	ES-FR	5.00	LT-LV	0.95
CZ-DE	2.10	ES-PT	4.20	LT-PL	0.50
CZ-PL	1.40	FI-NO	0.00	LT-SE	0.70
CZ-SK	1.80	FI-SE	2.40	LV-SE	0.00
DE-DK	4.70	FR-GB	0.00	NL-NO	0.70
DE-FR	3.30	FR-IE	0.00		
DE-LU	2.30	FR-IT	4.10		

Source: EMBER (2023); own assumptions.

4.2.3. Resource potentials

Wind & Solar

A country's wind and solar power potential is defined by (1) the achievable capacity factors at the respective sites and (2) the installable capacity of wind and solar power plants. The achievable capacity factors allow us to scale the hourly availability factors from Section 0. For capacity installed until 2020 we use historic availability factors between 2010 and 2020 for each technology and country (IRENA, 2025). For capacity built after 2030, we consider derived capacity factors from NREL (2013) for wind onshore and offshore and Pietzcker *et al.* (2014) for PV. For 2025, we assume an average between historical data and those for 2030-2050. Given the lack of data for CSP generation, we do not scale the hourly availability for this technology. The former sources are also used to estimate the installable capacity for these technologies.

To account for the varying quality of wind and solar sites within a country, we define three resource grades per intermittent renewable technology for every model region. Each resource grade comprises a certain share of the resource potential and its assigned average technology-specific capacity factor of this area. Table 17 shows the technologies' capacity potentials per model region; the corresponding capacity factors per region and resource grade are given in Table 18.

Table 17. Installable wind and solar power plant capacities per region and resource grade (in GW).

	Wind Onshore			Wind Offshore			PV			CSP		
	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
FI	--	5	253	--	29	51	69	278	333	--	1	3
NO	63	264	99	1	69	--	169	677	813	--	1	1
SE	--	40	316	--	155	67	92	367	440	1	2	4
EE	--	4	45	--	19	14	9	37	44	--	1	1
LV	--	4	67	--	38	28	19	75	90	--	1	2
LT	--	4	140	--	15	--	36	142	171	1	2	3
DK	--	106	--	74	146	--	31	124	148	1	2	3
GB	17	494	--	87	390	--	233	933	1120	3	10	21
IE	36	183	--	11	22	--	148	592	710	1	3	5
NL	--	35	44	3	159	--	31	125	150	--	1	2
PL	--	11	753	--	54	11	150	599	719	3	9	18
DE	--	73	496	16	74	2	230	921	1105	3	10	20
BE	--	6	65	--	16	--	33	131	157	--	1	2
LU	--	--	6	--	--	--	3	11	13	--	--	--
CZ	--	--	175	--	--	--	34	137	165	1	3	5
SK	--	--	105	--	--	--	24	95	114	--	1	2
AT	--	--	163	--	--	--	31	125	150	1	2	4
CH	--	--	60	--	--	--	23	91	109	--	1	2

	Wind Onshore			Wind Offshore			PV			CSP		
	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
HU	--	--	304	--	--	--	40	162	194	1	3	6
RO	--	--	653	--	--	48	155	619	743	3	8	17
SI	--	--	32	--	--	--	12	48	58	--	--	1
FR	--	85	1255	--	98	61	480	1921	2305	6	17	35
HR	--	--	135	--	--	36	7	30	36	--	1	2
BG	--	--	281	--	--	20	74	296	355	1	3	6
IT	--	--	700	--	--	77	218	872	1046	3	9	17
ES	--	11	1310	--	10	32	773	3093	3712	6	17	33
PT	--	--	195	--	--	9	171	685	822	1	2	4
GR	--	5	248	--	--	8	204	817	980	2	5	10
Balkan	--	--	535	--	--	1	37	149	179	2	6	12

Source: NREL (2013), Pietzcker *et al*. (2014), FAO (2018), Held (2010); own assumptions.

NREL (2013) provides global onshore and offshore wind supply curves based on the National Center for Atmospheric Research's (NCAR) Climate Four Dimensional Data Assimilation (CFDDA) mesoscale climate database. For onshore it provides the resource potential at different distances (0-50 miles [near], 50-100 miles [transitional] and 100-5000 miles [far]). Each of these areas is broken into nine resource grades according to an average capacity factor (0.16-0.48). Using only the resource potential for "near" areas, we aggregate these into only three resource grades and for each of them estimate the weighted average capacity factor and the total resource potential.

Likewise, for wind offshore, NREL (2013) provides the resource potential at different distances (5-20 miles [near], 20-50 miles [transitional] and 50-100 miles [far]). In this case, we use the data for areas "near" and "transitional" and estimate the capacity factors and resource potentials for three resource grades as for wind onshore.

For PV Pietzcker *et al.* (2014) provides the capacity factors of 9 resource grades (best 1%, 1% to 5%, etc) and the usable land for two type of areas (1-50 km from settlement and 50-100 km from settlement). We use the "1-50 km from settlement" data to estimate the capacity factors and installable potential of 3 resource grades aggregating the data from 0-5%, 5-25% and 25-100%.

For CSP, the installable capacity is determined by a set of three factors. First, by the area that is suitable for installing a specific technology. We derive the size of this area from land cover data (FAO, 2018). However, due to public acceptance and competing usage possibilities only a certain share of this area is actually available for power production; this share is the second determining factor. CSP plants may only be installed on former agricultural area, of which we assume that only the 2% is available for CSP installations (Held, 2010). And third, the amount of capacity that can be installed on the available area is subject to technology-specific restrictions. As we assume a SM4 configuration[19] in LIMES-EU, using data from Trieb *et al.* (2009) and Ong *et al.* (2013), we estimate the maximum installable capacity area to be 10 MW/km^2. The allocation of the resource potential into the three grades is made in a way that the first resource grade comprises the best resource sites of a region that together add up to 10% of the region's area. The second resource grade comprises the next best sites that add up to 30% of the region's area. Consequently, the third resource grade contains 60% of a region's area subsuming the sites with the lowest capacity factors.

Table 18. Maximum capacity factors of wind and solar power plants per region and resource grade (%).

	Wind Onshore			Wind Offshore			PV			CSP		
	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
FI	--	32	25	--	32	28	13	13	12	10	8	5
NO	40	34	26	40	35	--	11	10	9	12	10	4
SE	--	32	25	--	34	27	12	12	11	15	12	6

[19] See Section 0.

	Wind Onshore			Wind Offshore			PV			CSP		
	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
EE	--	32	28	--	32	28	13	13	13	13	13	12
LV	--	32	27	--	32	27	13	13	12	15	15	14
LT	--	32	28	--	32	--	13	13	12	17	16	15
DK	--	34	--	40	34	28	12	12	12	18	17	15
GB	40	34	--	40	36	--	12	10	9	23	20	15
IE	40	36	--	40	36	--	11	9	9	21	19	17
NL	--	34	28	40	36	--	11	11	10	22	21	20
PL	--	32	26	--	33	28	11	11	11	23	22	19
DE	--	33	25	40	35	28	12	11	10	26	24	20
BE	--	32	28	--	35	--	12	11	10	24	23	22
LU	--	--	25	--	--	--	11	10	10	24	24	23
CZ	--	--	24	--	--	--	11	11	10	25	24	23
SK	--	--	19	--	--	--	12	12	11	28	27	25
AT	--	--	22	--	--	--	13	12	12	29	28	26
CH	--	--	23	--	--	--	12	12	12	32	31	28
HU	--	--	18	--	--	--	13	12	12	32	31	28
RO	--	--	18	--	--	24	13	13	12	36	34	29
SI	--	--	17	--	--	16	14	13	13	32	31	30
FR	--	32	24	--	33	26	14	12	12	40	35	27
HR	--	--	18	--	--	18	14	13	12	38	35	32
BG	--	--	19	--	--	23	14	13	13	41	39	37
IT	--	--	19	--	--	17	17	15	14	53	44	35
ES	--	34	20	--	32	22	17	16	16	57	52	44
PT	--	--	22	--	--	25	18	16	15	55	52	46
GR	--	32	21	--	32	24	18	17	15	53	49	43
Balkan	--	--	18	--	--	24	14	13	13	43	39	35

Source: NREL (2013), Pietzcker *et al.* (2014); own assumptions.

Hydropower

Finally, the limited availability of sites suitable for deploying hydropower is reflected by a maximum installable capacity of hydropower plants. This is calculated based on the technically feasible hydropower potential, indicated in terms of maximum annual production by Eurelectric and VGB Powertech (2018). Given the lack of information regarding future changes in water inflows, we derive maximum installable capacity using historic availability factors for each country. Both installable capacities and annual availability factors are shown in Table 19.

Table 19. Hydropower potential.

	Installable capacity (GW)	Annual availability (%/a)		Installable capacity (GW)	Annual availability (%/a)
AT	11.4	56	IT	20.1	37
BE	0.2	33	LT	0.6	43
BG	7.8	22	LU	0	36
CZ	1.6	24	LV	2.2	21
DE	5.3	54	NL	0.1	31
DK	0	26	PL	3	46
EE	0	49	PT	9.5	29
ES	27.2	26	RO	15.4	30
FI	3.8	51	SE	31.5	47
FR	36.8	37	SI	2.2	45
GB	1.7	36	SK	2.4	31
GR	10.2	22	Balkan	0	41
HR	3.3	42	CH	13.5	35
HU	1.1	47	NO	66.3	52
IE	0.4	36			

Source: Open Power System Data (2018), EEA (2006), FAO (2018), ENTSO-E (2019), European Commission (2013), Eurelectric and VGB Powertech (2018), IRENA (2017); own assumptions.

Biomass

We pay particular attention to biomass because this might play a key role in emission reductions in the EU ETS as BECCS is the only generation technology considered that could generate negative emissions. Based on the available data and sustainability criteria, the ENSPRESO database (Ruiz Castello et al., 2019) and the Impact Assessment (IA) 2024 (European Commission, 2024) were identified as the most reliable data sources. A comparison of both studies' characteristics is presented in Table 20. While the ENSPRESO database offers highly detailed information, including biomass potentials by commodity and country, it falls short in aligning with the sustainability criteria of Renewable Energy Directive (RED II) (European Union, 2024) and the EU's Fit for 55 package. To address this, the total potentials from the IA 2024 are used to scale the ENSPRESO data, and thus derive more accurate potentials at country level. Given that the ENSPRESO database provides a more granular breakdown of biomass commodities than the IA 2024, we map the biomass types to make the data comparable.

Table 20. Comparison of biomass potentials per type from ENSPRESO (Ruiz Castello et al., 2019) and the IA 2024 (European Commission, 2024), in PJ.

	2040		2050	
	ENSPRESO	IA 2024	ENSPRESO	IA 2024
Agriculture residues	1359	1508	1259	1257
Food crops	1503	210	1538	42
Forestry	3645	2388	3150	1718
Lignocellulosic crops	1609	2556	1902	2472
Waste	469	3017	492	3226
Total	**8585**	**9679**	**8340**	**8757**

We choose the low scenario from ENSPRESO and the S2 scenario from the IA 2024. The low scenario was chosen as it applies the strictest sustainability criteria related to land use, agricultural practices, and protected areas of all three scenarios. Of all IA 2024 scenarios, S2 allocates the potentials to the biomass types in a way most closely aligned with the low scenario. Further, it focuses on reducing GHG emissions in the land sector including non-CO2 emissions in agriculture and carbon removals in LULUCF sector. In comparison, S1 is less ambitious and the LIFE scenario reckons with lower demand due to behavioural change. Both ENSPRESO database and the IA 2024 provide data for 2030, 2040 and 2050. We interpolate for intermediate years and assume potentials after 2050 equal to those in 2050. Figure 7 illustrates the estimated total biomass potentials in 2050.

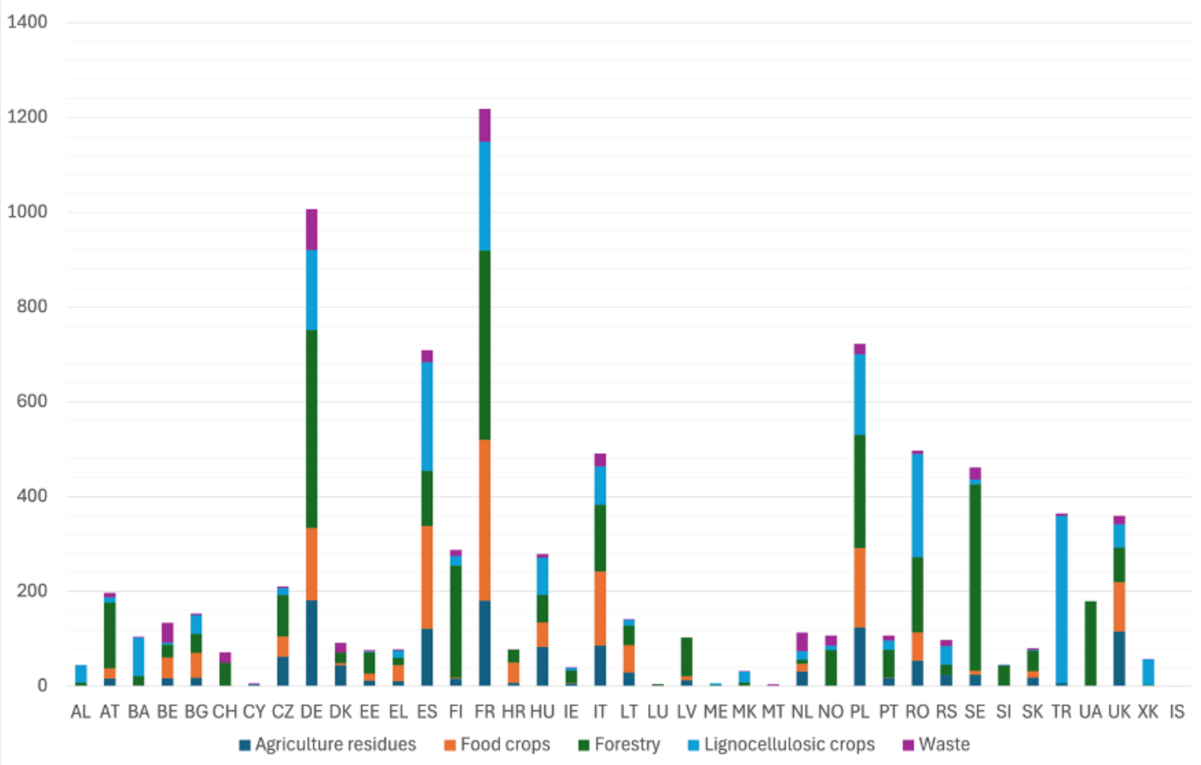


Figure 7. Estimated biomass potential in 2050.

As LIMES-EU does not capture the full energy system, it cannot endogenously represent the competition for biomass to be used for the production of liquid fuels, hydrogen, gases, heat and electricity, but rather needs assumptions on the amount of biomass that will be available for the power sector. Needless to say, the model does not cover other sectors competing for biomass use such as agriculture and food systems. We therefore use the maximum historic use of biomass (as a share of total biomass use) between 2010 and 2022 to scale further biomass potentials, i.e., estimate the maximum primary energy available for the power sector.

Nuclear and Fossil Thermal Plants

As stated in Section 0, fuel prices vary only slightly across regions (use of markups to improve calibration for 2015). However, the availability of certain fuels differs largely across regions. Hard coal, natural gas and uranium are available to every model region in unrestricted quantities. Lignite, waste and other gases, however, can only be consumed in their country of origin. LIMES-EU does not allow for trade of these fuels as their calorific value is too low for a cost-efficient long-distance transport. Given lack of data, we do not assume any constraint on lignite potential, but the associated generation technologies are strongly constrained by phase-out plans and exogenous capacity additions. We assume a potential of 20% more over the maximum historical primary energy between 2010 and 2020 (Eurostat, 2024) for waste and other gases.

5. Energy-intensive industry

While most EU ETS sectors are modelled through marginal abatement cost curves, the steel sector is represented with a detailed bottom-up module. This allows for explicit modelling of technology-specific investments, production, emissions, and fuel use. Steel interacts with the rest of the model in two main ways: (i) its electricity and hydrogen demand affects system-wide power investments and prices, and (ii) its direct fossil fuel use contributes to total EU ETS emissions, which are constrained by the EU-wide cap and banking rules.

5.1. Steel module

The steel module includes four production routes—BF-BOF, EAF, NG-DRI-EAF, and H2-DRI-EAF—each with specific requirements for fossil fuels, electricity, scrap, and hydrogen, as specified in Table 21. We typically assume steel demand is met at European level, and therefore technologies compete for market share based on cost, which includes investment, fixed, and variable O&M costs (see Table 22). Plants may be newly built or refurbished (relined), with the latter incurring only 50% of the CAPEX, reflecting industry practice.

Table 21. Energy carriers and materials input, as well as carbon intensity for producing steel through different technologies..

Technology	Gas	Coal	Coke	Electricity	Hydrogen	Scrap	CO2 intensity
	GJ/t-CS	GJ/t-CS	GJ/t-CS	GJ/t-CS	GJ/unit prod	t-scrap/t-CS	tCO_2/t-CS
BF_BOF	0.61	4.37	11.65	0.00	0.00	0.17	1.56
EAF	1.61	0.17	0.00	2.46	0.00	1.12	0.11
NG-DRI-EAF	10.58	0.00	0.00	2.47	0.00	0.17	0.59
H_2-DRI-EAF	2.03	0.00	0.00	2.47	6.89	0.17	0.11

Source: Agora Industrie et al. (2022) and Cappel (2021); Own unit conversion where applicable.

Table 22. Investment, fixed and variable costs for the different steelmaking technologies.

proc_LIMES	Investment costs (new – refurbished)	Fixed O&M costs	Var. O&M costs
	Eur/t-CS	(% investment costs)	Eur/t-CS
BF_BOF	159 – 80	0.3%	239
EAF	169 -84	0.3%	58
DRI_EAF_NG	698 – 349	0.3%	279
DRI_EAF_H2	698 - 349	0.3%	279

Source: Agora Industrie et al. (2022), Cappel (2021) and Material Economics (2019)

Different constraints are formulated to represent more accurately the steel capacity expansion, considering the particularities of this industry, e.g., the possibility to almost indefinitely refurbish these plants at a portion of the investment costs, the lump nature of investments, the barriers due to required infrastructure, and scrap availability. These restrictions are formalised in Appendix A.j. A complete list of assumptions and parameters, including fuel and scrap prices, depends on specific applications of this module.

5.2. Other industries

To estimate the costs of emission reductions in the energy-intensive industry, we rely on a marginal abatement cost curve (MACC). Originally, this MACC also includes the steel sector. Therefore, we scale down this curve when the steel module is included in the desired scenario (for computational reasons). For this aim we shrink the abatement potential by a factor equal to the share of the steel sector emissions in total ETS industry emissions. Otherwise, the MACC is fully included.

We base our approach on a study by the Federation of German Industries (BDI) (Gerbert et al., 2018), which provides a MACC for the German industry by 2050. This comprises 33 abatement options, which, without considering those electricity-related, add up to 175 $MtCO_2$ abatement potential in 2050 (i.e., baseline emissions), of which ~85% can be achieved at a price lower than 100 €/tCO_2. In the medium term this MACC constitutes nonetheless a very optimistic picture compared to recent estimates (Rehfeldt et al., 2020). They estimate that even assuming early replacement of the technology stock (fossil-based heating technologies are replaced when they reach 75% of their technical lifetime between 2025 and 2030), required carbon prices to reach a 15% emission reduction by 2030 amount to 175 €/tCO_2.

Due to the long-term perspective of LIMES-EU, we upscale the BDI MACC (Gerbert et al., 2018) to the entire EU ETS, assuming that the share of energy use from each sector and country remains unchanged over time and that other countries' emission factor changes in the same proportion as the German one. Through this approach, we estimate a total abatement potential of 701 $MtCO_2$ for the industries covered by the EU ETS. To estimate the MACC for each time step, we scale the MACC based on the 2015 total emissions from EU ETS industry (637 $MtCO_2$[20]) (European Commission, 2019). Since the marginal abatement costs do not appear plausible for current industrial deployment, we adjust them using data from and Enerdata (2020). Accordingly, we triple the costs for the period 2015-2030 and then by a factor progressively decreasing to 1 in 2050 (see Figure 8). We also assume a minimum cost of 8

[20] Estimating the emissions from energy-intensive industry covered by the EU ETS is not straightforward, as there could be mismatches in the sectors to which emissions are allocated. Combustion of fuels, accounting mainly for the power sector, emitted 1213 MtCO2, while other stationary emitted 590 MtCO2 (EEA, 2019). Since Mantzos et al. (2018) report 1166 MtCO2 for the power sector in 2015, we assume the difference between the 'combustion of fuels' and the power sector (47 MtCO2) correspond also energy-intensive industries. Hence, we estimate emissions from energy-intensive industries to be 637 MtCO2 in 2015.

€/tCO_2, equivalent to the assumed carbon price for 2015. Finally, we the same MACC as that for 2050 for the period afterwards.

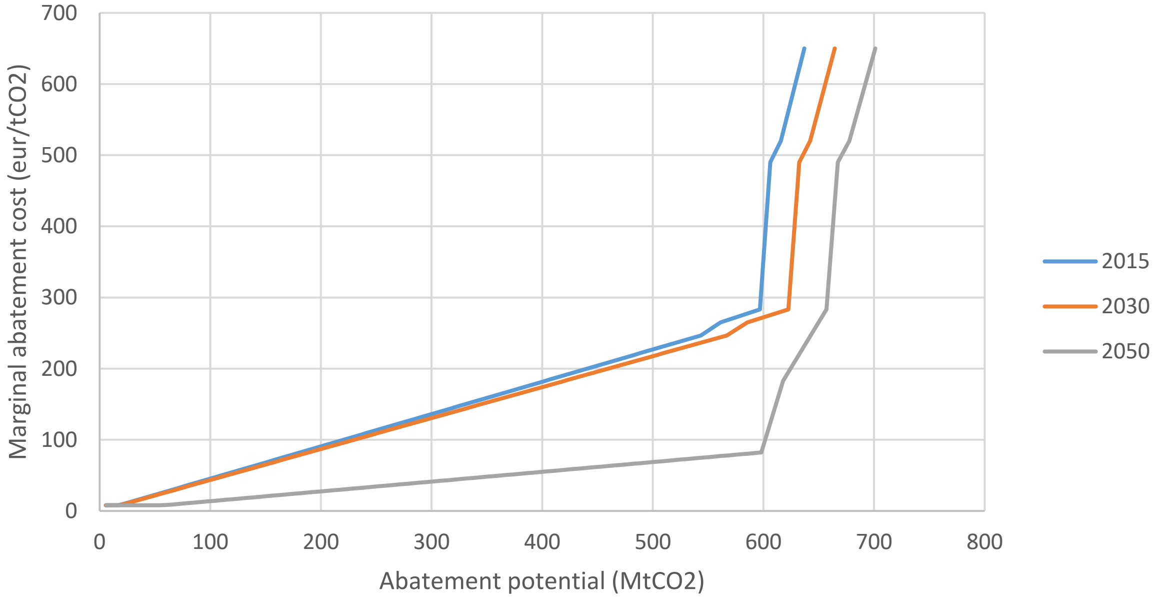


Figure 8. Estimated MACC in 2050 for the energy-intensive industry covered by the EU ETS.

6. Other EU ETS sectors

In order to represent the entire EU Emission Trading System (EU ETS) emissions from heating (large plants such as cogeneration heat and power (CHP) and district heating), aviation, the maritime sector, and the energy-intensive industry need to be considered as well. For heating, aviation, and maritime sectors, we assume exogenous emissions, estimated as shares deducted directly from the emission cap., while for the energy-intensive industry we derive a marginal abatement cost curve (MACC) to roughly model its emissions and abatement costs.

6.1. Heating

Heat-related emissions, i.e., from district heating plants, amounted to 212 MtCO_2 in 2015 (Mantzos et al., 2018). These emissions result from (large) heat-only plants and CHP which are connected to a district heating network. CHP emissions are typically allocated according to the electricity and heating output. At the moment, LIMES-EU assumes only electricity-only plants, therefore we represent heat-related emissions using a stylised approach. We derive a linear marginal abatement cost curve, which we calibrate to 2015 data. Correspondingly, the lowest cost equals the carbon prices in 2015 (8 EUR/t). We estimate the highest abatement cost at roughly 200 EUR/t. District heating demand is assumed to increase linearly to up to 20% in 2050 (see Figure 9). Due to the linear nature of LIMES-EU, we just assume a step-wise marginal abatement curve.

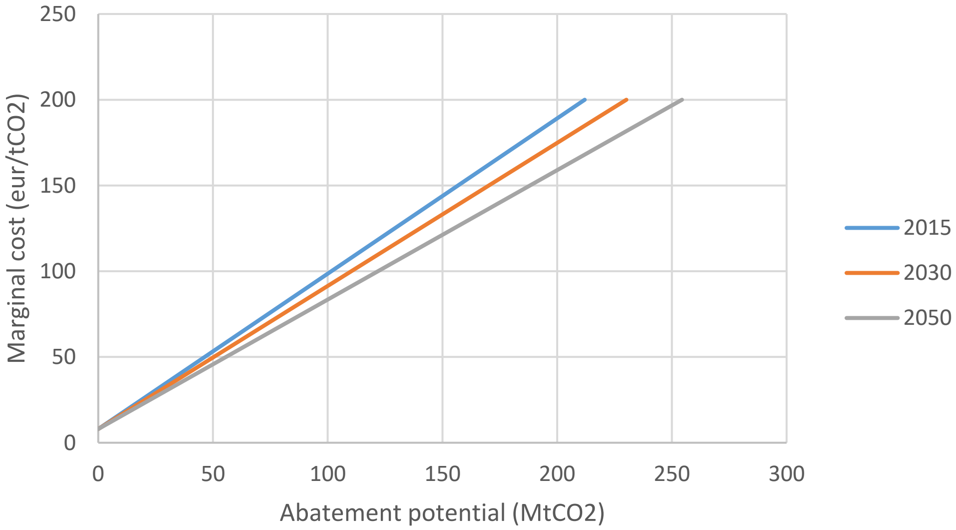


Figure 9. Estimated MACC in 2050 for the heating-related emissions covered by the EU ETS.

6.2. Aviation

This sector has its own cap, but is allowed to buy certificates from the stationary sector, and since the last EU ETS Directive, stationary installations there is full fungibility between stationary and aviation allowances. Therefore, we include emissions from this sector in the banking emissions constraint representing inter-temporal trading of allowances. Emissions are modelled through a marginal abatement cost curve, whose components we elaborate on as follows.

We estimate reference emissions (i.e., resulting emissions in the absence of carbon prices) based on flights data from the Aviation Outlook 2050 (EUROCONTROL, 2022). Since not all these flights are covered by the EU ETS, we need to estimate future reference emissions. From the number of flights and aviation emissions covered by the EU ETS between 2014 and 2022, we estimate an emission factor per flight. Based on a flight projection under different scenarios (low, base, high), we derive potential pathways for reference emissions (see Figure 10).

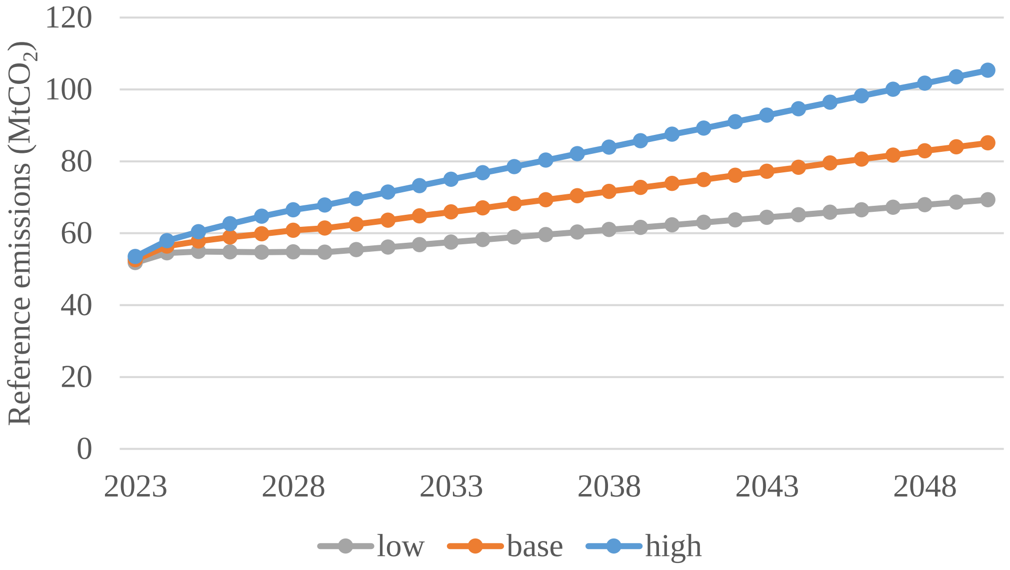


Figure 10. Estimated reference emissions for the aviation industry until 2050. Based on flights data (EUROCONTROL, 2022) and historic aviation emissions in the EU ETS (EEA, 2024).

As for the abatement costs and potentials, we derive a MACC based on van Geuns (2021). He provides abatement costs for different alternatives, namely sustainable aviation fuels (SAF), among which power to liquids coupled with DAC. Since DAC is included in the model, these alternatives are not considered. The three non-dominated approaches are Hydrotreated Esters and Fatty Acids (HEFA) - used cooking oil, Hydrothermal liquefaction (HTL) of forestry residues, and Fischer-Tropsch (FT) forestry residues. These SAF are constrained by their abatement potentials and emissions savings with respect to kerosene. Their marginal costs (adjusted to EUR2010) are shown in Figure 11 and their potentials in Table 23. Since potentials are lower than reference emissions, any residual emissions would need to be balanced by CDR (endogenous in the model).

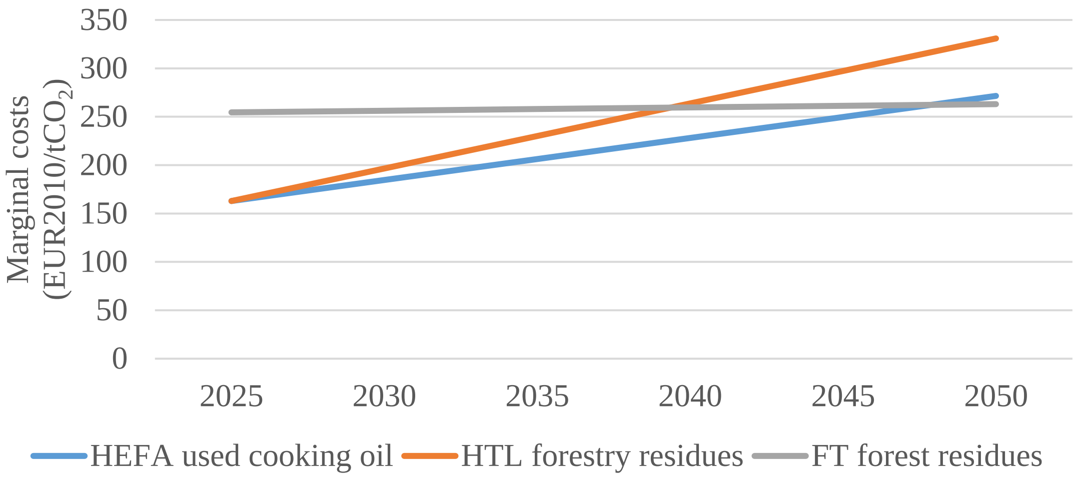


Figure 11. Marginal abatement costs in industry. Source: van Geuns (2021); own assumptions.

Table 23. SAF potentials.

	Abatement potential ($MtCO_2$/yr)	Emissions savings wrt kerosene
HEFA used cooking oil	3	85%
HTL forestry residues	40.6 in 2025; 69.3 afterwards	78%
FT forestry residues		From 110% in 2025 to 92% in 2050 (assumed to decrease linearly)

6.3. Maritime sector

This sector will be gradually included in the EU ETS until 2026, the share of allowances to be surrendered increasing as of 2024 (40% for 2024 emissions, 70% for 2025 emissions and 100% of 2026 emissions) (European Commission, 2021c). The EU estimates covered emissions to be around 90 $MtCO_2$ in year 2024 (European Commission, 2021c). There is significant uncertainty about future emissions – the worldwide demand for shipping is projected to grow, while the shift to cleaner technologies is still in an emergence phase, making it unlikely to reach a large-scale decarbonization before 2040 (Domagoj Baresic and Katharine Palmer, 2021).

As for energy-intensive industry, district heating and aviation, we derive a marginal abatement cost curve for the maritime sector. Reference emissions are derived from Transport & Environment (2022). Marginal costs are based on Parker et al. (2021). From visual inspection and some own assumptions, we can derive a MACC for shipping. We do not consider differences in vessels used for intra-EU and extra-EU shipping, but costs need to be adjusted based on the share of emissions that are covered in each intra and extra-EU shipping: 100% of emissions from the former while only 50% of emissions from the latter need to be covered with EU allowances. This implies that abatement alternatives are only deployed in extra-EU shipping when EUA prices double the abatement costs. A further adjustment is required given the expected cost decrease in the long term. Parker et al. (2021) report costs on the lower end of the original data (Smith et al., 2019). More, specifically, maximum costs in Smith et al. (2019) are around 500 EUR/tCO2, i.e., x2.5 maximum costs reported in Parker et al. (2021). We thus adjust costs until 2030 by a factor of 2.5, which linearly decreases to 1 by 2050.

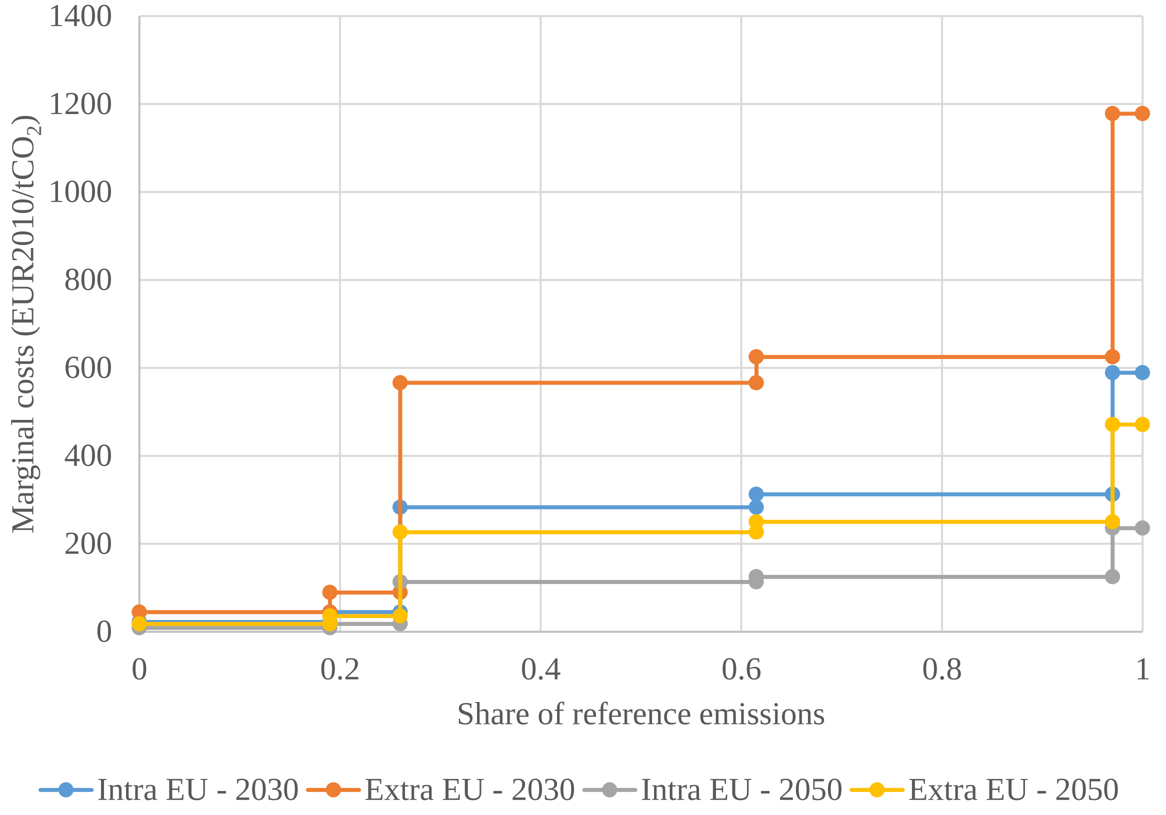


Figure 12. Marginal abatement costs for intra- and extra-EU shipping in 2030 and 2050. Source: Parker et al. (2021) and Smith et al. (2019); own assumptions.

7. Direct air carbon capture and storage (DACCS)

In the model we only consider DACCS and BECCS, which are the most mature options and the main technologies for capturing carbon permanently. By including them in the model, we can determine the extent of the EU ETS's role in promoting CDR implementation. BECCS also generates electricity, so its parameters are already discussed in Section 0. In this section we focus on DACCS technologies.

We consider three DACCS technologies: Liquid solvent, Solid sorbent and CaO ambient weathering- Their operation differs mainly on the fuels consumed (see Table 24). All parameters are derived from Sievert et al. (2024), who conducted a bottom-up calculation of these costs for pioneering DAC plants, including carbon transport and storage. Sievert et al. (2024) project costs using multi-component experience curves, considering the technological characteristics of individual components within these DACCS plants. By applying projected technology shares to global deployment scenarios from Grant et al. (2021), they derive cost pathways over time for each technology. Sievert et al. (2024) only report levelized removal costs, which already include assumptions on electricity costs. Since electricity costs are endogenous to LIMES-EU, the authors provide capital, fixed, and operational costs for these technologies as part of a joint work in progress. Table 25 presents the cost assumptions. In addition to these costs, we assume a CO_2 transport and storage cost dependent on country and varying over time (see Figure 13), which also applies to carbon captured by BECCS.

Table 24. DACCS operational parameters.

Parameters	Liquid solvent DACCS	Solid sorbent DACCS	CaO ambient weathering
Electricity consumption (GJ/tCO_2-removed)	1.3	5.9	9.0
Gas consumption (GJ/tCO_2-removed)	5.3	--	--
Minimum capacity factor	0.50	0.75	0.50
Maximum capacity factor	0.90	0.90	0.90

Source: Sievert et al. (2024)

Table 25. DACCS costs assumptions.

	2025	2030	2035	2040	2045	2050 - 2070
CAPEX (EUR/tCO_2-capacity)						
Liquid solvent DACCS	2604	2194	1848	1557	1312	1105
Solid sorbent DACCS	2053	1799	1577	1382	1211	1061
CaO ambient weathering	9107	7320	5883	4728	3800	3054
Fixed costs (% CAPEX)						

Liquid solvent DACCS	4%	4%	4%	4%	4%	4%
Solid sorbent DACCS	4%	4%	4%	4%	4%	4%
CaO ambient weathering	3%	3%	3%	3%	3%	3%
Variable costs (EUR/tCO_2-removed)						
Liquid solvent DACCS	94	89	85	81	77	73
Solid sorbent DACCS	2	2	2	2	2	1
CaO ambient weathering	1	1	1	1	1	1

Source: Sievert et al. (2024)

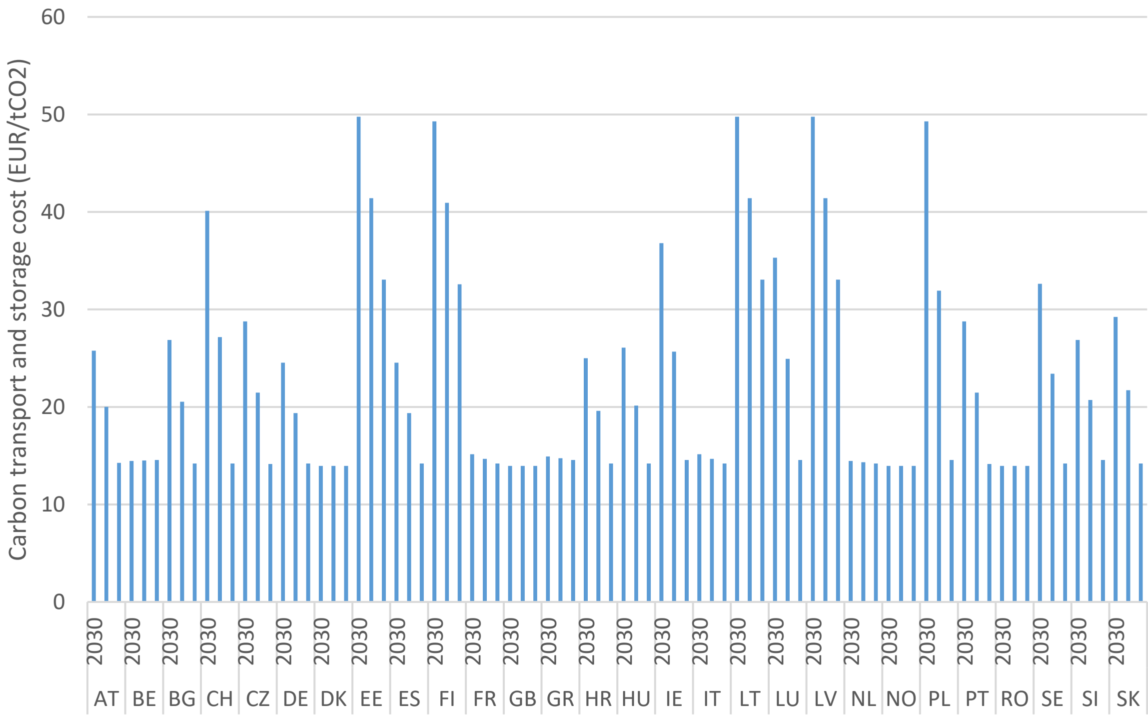


Figure 13. Costs of transporting and storing CO2 for all countries between 2030 and 2050. Values after 2050 are considered to continue at 2050 levels. Data provided by Katrin Sievert.

8. Implementation of Policies

The model allows for implementing climate and energy policy targets by including constraints on CO_2 emissions or on the deployment of certain technologies. Targets can be set for single countries or for aggregate regions such as the EU Member States. As LIMES-EU is a social planner optimization model with perfect foresight, policy targets will always be achieved in a cost-effective way. Hence, results from LIMES-EU provide useful benchmarks on the future development of the European electricity system, but potentially underestimate important obstacles such as public acceptance or institutional capacity (cf. Hughes and Strachan (2010)).

Climate Policy Different stylized policies can be implemented in LIMES-EU (emission intensity, CO_2 taxes, emission caps and budgets) for different countries, regions and primary energy sources. However, in a typical setup, we model the EU ETS with its main features, namely inter-temporal trading and the Market Stability Reserve (MSR) (see Appendix A.h). The emissions cap is always defined according to the research question, but currently representing the most updated policy state, e.g., the 'Fit for 55' package.

Renewable Policy LIMES-EU allows for implementing technology-specific renewable energy targets for single model regions and implementing overall RES targets on EU or country level. Targets are implemented as lower bounds on electricity production from these technologies.

Energy Efficiency Policy Energy efficiency translates to less electricity demand than the reference scenario. As the electricity demand is given exogenously its reduction is not part of the optimization but set exogenously as well.

Nuclear, Coal & CCS-related Policies In several countries nuclear power plants, coal-fired plants and CCS technology face problems in public acceptance e.g. due to environmental risks. To accommodate this, their future deployment can be constrained by upper limits on investments or on capacity directly. These limits can be set for each model region separately.

9. Evaluating base-year results

Validating a long-term social planner model is conceptually challenging as the model does not aim to replicate historic developments but is designed to generate a socially optimal benchmark without considering real-world market failures. A full-fledged validation is beyond the scope of this document. Nevertheless, complementary to the documentation of the model structure and its parameter values, this Section aims to build further trust in the model and to make its reasoning more accessible.

We calibrate the model by fixing electricity, storage and transmission capacities from 2010 to 2020 based on historical data, and scaling levels if required to align with historic electricity generation. In contrast, electricity dispatch, and thus its related emissions, and emissions from other sectors, remain completely endogenous in the model.

Focusing on capturing EU ETS dynamics, we compare modelled emissions with historical emissions for 2020, as shown by Figure 14. As can be seen, both modelled and historical emissions are approximately equal. The sectoral split of emissions differs somewhat because the source for historical emissions (EEA, 2024) uses slightly different categories. That is, 'Combustion of fuels' comprises power sector emissions as well as some industry emissions. The rest of industry emissions are reported as 'All industrial installations (excl. combustion)'. Since the modelled industry emissions are slightly higher than the reported "All industrial installations (excl. comb)" value, our modelled emissions align with historical ones.

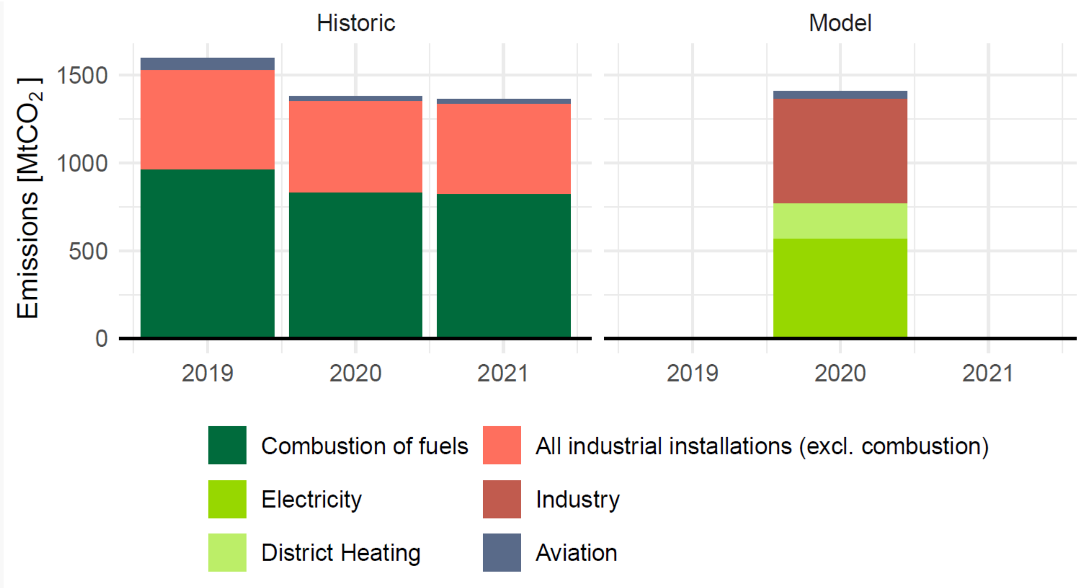


Figure 14. Comparison of historic and modelled EU ETS emissions. Source: EEA (2024) and model results.

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Appendix

A. Mathematical Model

a. Sets, Indices, Parameters and Variables

Table A1 to Table A4 give an overview about the symbols for indices, sets, parameters and variables used in the equations. All variables are constrained to be non-negative.

Table A1. Indices.

Symbol	Description
t, tt	years
day	days
τ	time slices
r	regions
rg	vRES resource grades
te	electricity generation technologies
ti	Industry technologies
st	storage technologies
cn	transmission connections
pe	primary energy types
s	sector (e.g., electricity)
m	abatement measure
i	material and fuel input for industry

Table A2. Sets.

Symbol	Description
R	all regions
R^{pol}	regions with a common policy
T^{ETS}	year until the EU ETS operates
T	all time slices
T_{day}	time slices of a specific *day*

Symbol	Description
TE	all electricity generation technologies
TE_{pe}	electricity generation technologies working with a specific *pe*
TE_{pe}^{CCS}	CCS equipped electricity generation technologies working with *pe*
TE^{disp}	dispatchable electricity generation technologies
TE^{ramp}	thermal electricity generation technologies with ramping constraints
TE^{RES}	RES technologies
TE^{vRES}	vRES technologies
ST	all storage technologies
$ST^{seasonal}$	interday storage technologies
$ST^{intraday}$	intraday storage technologies
CN	all transmission connections
CN_r^{out}	transmission connections defined as starting in region *r*
CN_r^{in}	transmission connections defined as ending in region *r*
M_s	Abatement measure in sector s (for ETS sectors whose emissions are represented by a MAC, i.e., industry and heat)
TE^{DH}	District heating technologies
TI	all industry technologies
TI^{steel}	Steelmaking technologies
$TI_{BF-BOF}^{steel}, TI_{EAF}^{steel}, TI_{DRI-EAF}^{steel}$	Subsets of BF-BOF, EAF, DRI-EAF technologies
$TI_{new}^{steel}, TI_{ref}^{steel}$	Subset of new (i.e., full CAPEX) and refurbished/re-lined (i.e., reduced CAPEX) technologies
S_{input}^{steel}	Set of all inputs in industry: fuels, electricity, hydrogen, scrap, etc.

Table A3. Parameters.

Symbol	Description
ρ	discount rate
Δt	time span (in years) between model years
l_τ	length of time slice τ
λ_{pe}	emission factor of primary energy *pe*
$\psi_{te}, \psi_{st}, \psi_{cn}$	lifetime of technology *te* / storage *st* / connection *cn*
μ_{te}	minimum load of technology *te*
δ	minimum annual load
φ_r	minimum share of domestic electricity supply for region *r*
$c^I_{t,te}, c^I_{t,st}, c^I_{t,cn}$	power capacity investment cost
$c^{IR}_{t,st},$	reservoir capacity investment cost
$c^F_{t,pe}$	fuel cost
$c^{OMF}_{te}, c^{OMF}_{st}$	fixed operation and maintenance cost
$c^{OMV}_{te}, c^{OMV}_{st}$	variable operation and maintenance cost
$c^{CO_2}_{t,r,s}$	CO_2 emission cost
$macc^{CO_2}_{t,r,s,m}$	marginal abatement costs in sector s
$abat^{CO_2}_{t,r,s,m}$	abatement potential in sector s (i.e., baseline emissions)
$v_{\tilde{t},te}, v_{\tilde{t},st}, v_{\tilde{t},cn}$	salvage value factor
$\omega_{\tilde{t},te}, \omega_{\tilde{t},cn}$	depreciation factor
$d_{t,\tau,r}$	electricity demand
$\alpha^{vRES}_{\tau,r,te,rg}, \alpha_{r,te}, \alpha_{\tau,r,te}\ \alpha_{cn}$	availability factor
η_{te}, η_{st}	conversion efficiency
γ_{cn}	transmission losses
$p^{max}_{t,r,pe}$	maximum primary energy consumption
$cap^{CCS_{cum}}_r$	maximum CCS storage capacity
$res_{t,r}$	target for minimum electricity production from RES
$cap^{CO_2}_t, cap^{CO_2}_{t,r}$	CO_2 emissions cap
bud^{CO_2}, bud^{CO_2}	CO_2 emissions budget
$cap\_avi^{CO_2}_t$	CO_2 emissions cap for the aviation sector

Symbol	Description
$euaa_t^{CO_2}$	EU allowances used by the aviation sector
$e_{t,avi}^{CO_2}$	CO_2 emissions from the aviation sector
$cap\_mar_t^{CO_2}$	CO_2 emissions cap for the maritime sector
$euam_t^{CO_2}$	EU allowances used by the maritime sector
$e_{t,mar}^{CO_2}$	CO_2 emissions from the maritime sector
a_{te}	auto-consumption rate
r_{te}	ramping factor
f_{te}, f_{st}	firm capacity factor for *te*, *st* and imports
rm	reserve margin
ϑ^{RK}	maximum share of reserves in demand
μ	minimum share of hydrogen produced by electrolysis within the model regions
θ	number of cycles in hydrogen storage
$h_{t,r}^{OS}$	hydrogen demand from other sectors
ψ_{ti}	Lifetime of industry technology *ti*
$\beta_{ti,i}$	Consumption of all inputs per unit of production
κ^{steel}	Maximum industry capacity additions between two periods
$ScrapAvail_t$	Scrap availability

Table A4. Variables.

Symbol	Description
C^{tot}	total system cost
C_t^I	investment cost
C_t^F	fuel cost
C_t^{OM}	operation and maintenance cost
$C_t^{CO_2}$	CO_2 emission cost
$A_{t,r,s,m}^{CO_2}$	abatement in sector s by implementing measure *m*
V	salvage value
$PE_{t,r,te}$	primary energy consumption

Symbol	Description
$K_{t,r,te}$, $K_{t,r,st}$, $K_{t,cn}$	installed capacity
$\Delta K_{t,r,te}$, $\Delta K_{t,r,st}$, $\Delta K_{t,cn}$	new capacity
$SK_{t,r,st}$	reservoir capacity
$\Delta SK_{t,r,st}$	new reservoir capacity
$K^{RG}_{(t-\tilde{t}),r,te,rg}$	installed capacity (resource grade specific)
$\Delta K^{RG}_{(t-\tilde{t}),r,te,rg}$	new capacity (resource grade specific)
$G_{t,\tau,r,te}$	electricity generation
$E^{CO_2}_{t,r,s}$, $E^{CO_2}_{t,s}$	CO_2 emissions
$E^{CCS}_{t,r,elec}$	captured CO_2 (via CCS)
$S^{IN}_{t,\tau,r,st}$, $S^{OUT}_{t,\tau,r,st}$	storage input/output
$L_{t,\tau,r,st}$	storage level
$F^{+}_{t,\tau,cn}$, $F^{-}_{t,\tau,cn}$	transmission flow in positive / negative direction
$OP_{t,\tau,r,te}$, $OP_{t,day,r,te}$	operating (running) capacity
$RK_{t,r,te}$	reserve capacity
$Ramp_{t,\tau,r,te}$	maximum generation variation between two time slices
$DK_{tt,t,r,te}$, $DK_{tt,t,cn}$	disinvestment (decommissioning) in *t* of capacity built in *tt*
$DK^{RG}_{tt,t,r,te,rg}$	disinvestment in *t* of capacity built in *tt* (resource grade specific)
$TNAC^{CO_2}_{t}$	total number of allowances in circulation in EU ETS
$H^{EL}_{t,\tau,r}$, $H^{OS}_{t,\tau,r}$	hydrogen produced by electrolysis for the electricity sector (EL) and for other sectors (OS)
$IH^{EL}_{t,r}$, $IH^{OS}_{t,r}$	hydrogen imported for the electricity sector (EL) and other sectors (OS)
$SupEUA^{CO_2}_{t}$	supply of EUA
$FreeEUA^{CO_2}_{t}$	free-allocated EUA
$AucEUA^{CO_2}_{t}$	auctioned EUA
$Emi^{CO_2}_{t}$	EUA rendered to the EU ETS
$Q^{steel}_{t,r,ti}$	Steel production

Symbol	Description
$\Delta K_{t,r,ti}^{steel}$	Steel capacity additions
$K_{t,tt,r,ti}^{steel}$	Steel installed capacity
$DK_{t,tt,r,ti}^{steel}$	Steel capacity decommissioning

a. Objective function

Equation (A.1): Objective function

$$C^{tot} = \sum_{t} \left(\Delta t \; e^{-\rho(t-t_0)} \left(C_t^I + C_t^F + C_t^{OM} + C_t^{CO_2} \right) \right) - e^{-\rho(t_{end}-t_0)} V \tag{A.1}$$

Equation (A.2): Fuel costs (some of the hydrogen might be produced by electrolysis [internal to the model])

$$C_t^F = \sum_{r,pe|pe \neq \{hydrogen\}} c_{t,pe}^F PE_{t,r,pe} + c_{t,pe|pe=\{hydrogen\}}^F \sum_{r} \left(IH_{t,r}^{EL}, IH_{t,r}^{OS} \right) \qquad \forall t \tag{A.2}$$

Equation (A.3): Investment costs

$$C_t^I = \sum_{r,te} \left(c_{t,te}^I \Delta K_{t,r,te} \right) + \sum_{r,st} \left(c_{t,st}^I \Delta K_{t,r,st} \right) + \sum_{r,st} \left(c_{t,st}^{IR} \Delta SK_{t,r,st} \right) + \sum_{cn} \left(c_{t,cn}^I \Delta K_{t,cn} \right) \qquad \forall t \tag{A.3}$$

Equation (A.4): Operation and maintenance costs

$$C_t^{OM} = \sum_{r,te}\left(c_{te}^{OMF} c_{t,te}^{I}\left(K_{t,r,te} + RK_{t,r,te}\right) + c_{te}^{OMV}\sum_{\tau} l_\tau G_{t,\tau,r,te}\right) + \sum_{r,st}\left(c_{st}^{OMF} c_{t,st}^{I} K_{t,r,st} + c_{st}^{OMV}\sum_{\tau} l_\tau S_{t,\tau,r,st}^{OUT}\right) \qquad \forall t \tag{A.4}$$

Equation (A.5): Emission costs

$$C_t^{CO_2} = \sum_{r}\left(\sum_{s} c_{t,r,s}^{CO_2} E_{t,r,s}^{CO_2} + \sum_{m,s|s\in\{heat,industry\}} macc_{t,r,s,m}^{CO_2} A_{t,r,s,m}^{CO_2}\right) \qquad \forall t \tag{A.5}$$

Equation (A.6): Salvage value

$$V = \Delta t\left(\sum_{te,r}\sum_{\tilde{t}=0}^{\psi_{te}} v_{\tilde{t},te} c_{(t_{end}-\tilde{t}),te}^{I} \Delta K_{(t_{end}-\tilde{t}),r,te} e^{\rho\tilde{t}\Delta t} + \sum_{st,r}\sum_{\tilde{t}=0}^{\psi_{st}} v_{\tilde{t},st} c_{(t_{end}-\tilde{t}),st}^{I} \Delta K_{(t_{end}-\tilde{t}),r,st} e^{\rho\tilde{t}\Delta t} + \sum_{cn}\sum_{\tilde{t}=0}^{\psi_{cn}} v_{\tilde{t},cn} c_{(t_{end}-\tilde{t}),cn}^{I} \Delta K_{(t_{end}-\tilde{t}),cn}\, e^{\rho\tilde{t}\Delta t}\right) \qquad \forall t \tag{A.6}$$

b. Electricity balance

Equation (A.7): Electricity balance

$$d_{t,\tau,r} = \sum_{te} G_{t,\tau,r,te} + \sum_{st \in ST^{intraday}} S^{OUT}_{t,\tau,r,st} - \sum_{st} S^{IN}_{t,\tau,r,st} + \sum_{cn \in CN^{in}_r} \left((1-\gamma_{cn}) F^{+}_{t,\tau,cn} - F^{-}_{t,\tau,cn} \right) + \sum_{cn \in CN^{out}_r} \left((1-\gamma_{cn}) F^{-}_{t,\tau,cn} - F^{+}_{t,\tau,cn} \right) \qquad \forall t, \tau, r \tag{A.7}$$

c. Equations for generation technologies

Equation (A.8): Expansion, decommissioning and depreciation of generation technologies

$$K_{t,r,te} = \Delta t \left(\sum_{\tilde{t}=0}^{\psi_{te}} \omega_{\tilde{t},te} \Delta K_{(t-\tilde{t}),r,te} - \sum_{(tt,\tilde{t}):(\tilde{t} \in (0,\psi_{te}) \cap tt > t-\tilde{t})} \omega_{\tilde{t},te} DK_{tt,(t-\tilde{t}),r,te} \right) \qquad \forall t, r, te \tag{A.8}$$

Equation (A.9): Expansion, decommissioning and depreciation of generation technologies per resource grade

$$K^{RG}_{t,r,te,rg} = \Delta t \sum_{\tilde{t}=0}^{\psi_{te}} \omega_{\tilde{t},te} \Delta K^{RG}_{(t-\tilde{t}),r,te,rg} - \Delta t \sum_{(tt,\tilde{t}):(\tilde{t} \in (0,\psi_{te}) \cap tt > t-\tilde{t})} \omega_{\tilde{t},te} DK^{RG}_{tt,t-\tilde{t},r,te,rg} \qquad \forall t, r, rg, te \in TE^{vres} \tag{A.9}$$

Equation (A.10): Expansion of vRES technologies in regions and resource grades

$$\Delta K_{t,r,te} = \sum_{rg} \Delta K^{RG}_{t,r,te,rg} \qquad \forall t, r, te \in TE^{vRES} \tag{A.10}$$

Equation (A.11): Decommissioning of vRES technologies in regions and resource grades

$$DK_{tt,t,r,te} = \sum_{rg} DK^{RG}_{tt,t,r,te,rg} \qquad \forall tt, t, r, te \in TE^{vRES} \tag{A.11}$$

Equation (A.12): Constraint on disinvestments

$$\sum_{tt} DK_{tt,t,r,te} \leq \Delta K_{t,r,te} \qquad \forall\ t, r, te \tag{A.12}$$

Equation (A.13): Constraint on disinvestments in resource grades

$$\sum_{tt} DK^{RG}_{tt,t,r,te,rg} \leq \Delta K^{RG}_{t,r,te,rg} \qquad \forall\ t, r, te \in TE^{vRES}, rg \tag{A.13}$$

Equation (A.14): Capacity constraint for dispatchable generation technologies

$$G_{t,\tau,r,te} \leq K_{t,r,te} \alpha_{\tau,r,te} (1 - a_{te}) \qquad \forall\ t, \tau, r, te \in TE^{disp} \tag{A.14}$$

Equation (A.15): Availability of Wind Onshore, Wind Offshore and PV

$$G_{t,\tau,r,te} \leq \sum_{rg} \alpha^{vRES}_{\tau,r,te,rg} K^{RG}_{t,r,te,rg} \tag{A.15}$$

$$\forall\ t, \tau, r, te \in \{Wind\ Onshore, Wind\ Offshore, PV\}$$

Equation (A.16): Availability of CSP

$$\sum_{\tau \in T_{day}} l_\tau G_{t,\tau,r,te} \leq \sum_{\tau \in T_{day}} l_\tau \sum_{rg} \alpha^{vRES}_{\tau,r,te,rg} K^{RG}_{t,r,te,rg} \qquad \forall\, t, day, r, te \in \{CSP\} \tag{A.16}$$

Equation (A.17): Annual availability of dispatchable generation technologies

$$\sum_{\tau} l_\tau G_{t,\tau,r,te} \leq \sum_{\tau} l_\tau \alpha_{r,te} K_{t,r,te} \qquad \forall\, t, r, te \in TE^{disp} \tag{A.17}$$

Equation (A.18): Minimum annual load for dispatchable generation technologies

$$\sum_{\tau} l_\tau G_{t,\tau,r,te} \geq \delta \sum_{\tau} l_\tau K_{t,r,te} \qquad \forall\, t, r, te \in TE^{disp} \tag{A.18}$$

Equation (A.19): Operation constraint for dispatchable generation technologies

$$OP_{t,\tau,r,te} \leq K_{t,r,te} \qquad \forall\, t, \tau, r, te \in TE^{disp} \tag{A.19}$$

Equation (A.20): Generation constraint for dispatchable generation technologies

$$G_{t,\tau,r,te} \leq OP_{t,\tau,r,te} \alpha_{\tau,r,te} (1 - a_{te}) \qquad \forall\, t, \tau, r, te \in TE^{disp} \tag{A.20}$$

Equation (A.21): Minimum load constraint for dispatchable generation technologies

$$G_{t,\tau,r,te} \geq \mu_{te} OP_{t,\tau,r,te} \qquad \forall\, t, \tau, r, te \in TE^{disp} \tag{A.21}$$

Equation (A.22): Operating capacity constraint for thermal generation technologies (except nuclear)

$$OP_{t,\tau\in T_{day},r,te} = OP_{t,day,r,te} \qquad \forall\ t,\tau,r,te \in TE^{ramp} \wedge te \neq Nuclear \tag{A.22}$$

Equation (A.23): Operating capacity constraint for nuclear power plants

$$OP_{t,\tau,r,te} = OP_{t,\tau+1,r,te} \qquad \forall\ t,\tau,r,te \in TE^{ramp} \wedge\ te = Nuclear \tag{A.23}$$

Equation (A.24): Ramping constraint for thermal generation technologies

$$G_{t,\tau\in T_{day},r,te} = G_{t,(\tau+1)\in T_{day},r,te} + Ramp_{t,\tau,r,te} \qquad \forall\ t,\tau,r,te \in TE^{ramp} \tag{A.24}$$

Equation (A.25): Ramping-up and -down constraint for thermal generation technologies

$$-OP_{t,\tau,r,te}r_{te} \leq Ramp_{t,\tau,r,te} \leq OP_{t,\tau,r,te}r_{te} \qquad \forall\ t,\tau,r,te \in TE^{ramp} \tag{A.25}$$

d. Equations for transmission technologies

Equation (A.26): Expansion and depreciation of transmission capacity

$$K_{t,cn} = \Delta t \left(\sum_{\tilde{t}=0}^{\psi_{cn}} \omega_{\tilde{t},cn} \Delta K_{(t-\tilde{t}),cn} - \sum_{(tt,\tilde{t}):(\tilde{t}\in(0,\psi_{cn})\ \cap\ tt > t-\tilde{t})} \omega_{\tilde{t},cn} DK_{tt,(t-\tilde{t}),cn} \right) \qquad \forall\ t,cn \tag{A.26}$$

Equation (A.27): Constraint on disinvestments of transmission capacity

$$\sum_{tt} DK_{tt,t,cn} \leq \Delta K_{t,cn} \qquad \forall\, t, cn \tag{A.27}$$

Equation (A.28): Transmission constraint

$$F^{+}_{t,\tau,cn} \leq \alpha_{cn} K_{t,cn} \qquad \forall\, t, \tau, cn \tag{A.28}$$

$$F^{-}_{t,\tau,cn} \leq \alpha_{cn} K_{t,cn} \qquad \forall\, t, \tau, cn$$

e. Equations for storage technologies

Equation (A.29): Expansion and depreciation of power capacity

$$K_{t,r,st} = \Delta t \left(\sum_{\tilde{t}=0}^{\psi_{st}} \omega_{\tilde{t},st} \Delta K_{(t-\tilde{t}),r,st} - \sum_{(tt,\tilde{t}):(\tilde{t}\in(0,\psi_{cn}) \,\cap\, tt > t-\tilde{t})} \omega_{\tilde{t},st} DK_{tt,(t-\tilde{t}),r,st} \right) \qquad \forall\, t, r, st \tag{A.29}$$

Equation *(A.30)*: Expansion of reservoir capacity

$$SK_{t,r,st} = \Delta t \left(\sum_{\tilde{t}=0}^{\psi_{st}} \omega_{\tilde{t},st} \Delta SK_{(t-\tilde{t}),r,st} \right) \qquad \forall\, t, r, st \tag{A.30}$$

Equation (A.31): Constraint on disinvestments of power capacity

$$\sum_{tt} DK_{tt,t,r,st} \leq \Delta K_{t,r,st} \qquad \forall\, t, cn \tag{A.31}$$

Equation (A.32): Power constraint

$$S_{t,\tau,r,st}^{IN} \leq K_{t,r,st} \qquad \forall\, t, \tau, r, st \tag{A.32}$$

$$S_{t,\tau,r,st}^{OUT} \leq K_{t,r,st} \qquad \forall\, t, \tau, r, st$$

Equation (A.33): Reservoir level

$$L_{t,\tau-1,r,st} + \eta_{st} l_\tau S_{t,\tau,r,st}^{IN} - l_\tau S_{t,\tau,r,st}^{OUT} = L_{t,\tau,r,st} \qquad \forall\, t, \tau, r, st \in ST^{intraday} \tag{A.33}$$

Equation (A.34): Constraint on reservoir level (intraday storage)

$$L_{t,\tau,r,st} \leq SK_{t,r,st} \qquad \forall\, t, \tau, r, st \in ST^{intraday} \tag{A.34}$$

Equation (A.35): Proxy for electrolysis reservoir capacity based on total demand and exogenous number of cycles (θ)

$$\sum_{\tau} l_\tau S_{t,\tau,r,st}^{OUT} \leq SK_{t,r,st} * \theta \qquad \forall\, t, r, st \in ST^{seasonal} \tag{A.35}$$

Equation (A.36): Seasonal storage balance (annual)

$$\eta_{st} \sum_{\tau} l_\tau S_{t,\tau,r,st}^{IN} = \sum_{\tau} l_\tau S_{t,\tau,r,st}^{OUT} \qquad \forall\, t, r, st \in ST^{seasonal} \tag{A.36}$$

Equation (A.37): Intraday storage balance (for each representative day)

$$\eta_{st} \sum_{\tau \in T_{day}} l_\tau S_{t,\tau,r,st}^{IN} = \sum_{\tau \in T_{day}} l_\tau S_{t,\tau,r,st}^{OUT} \qquad \forall\, t, day, r, st \in ST^{intraday} \tag{A.37}$$

f. Primary energy demand and CO_2 emissions

Equation (A.38): Primary energy demand

$$PE_{t,r,te} = \sum_{\tau} l_{\tau} \sum_{te \in TE_{pe}} G_{t,\tau,r,te} \Big/ \big(\eta_{te}(1 - a_{te})\big) \qquad \forall\, t, \tau, r, pe \tag{A.38}$$

Equation (A.39) : Primary energy constraint for certain energy carriers, e.g., lignite and biomass

$$PE_{t,r,pe} \leq p_{t,r,pe}^{max} \qquad \forall\, t, r, pe \tag{A.39}$$

Equation (A.40): Hydrogen used by hydrogen-based technologies, namely hydrogen CC (HCC), hydrogen CT (HCT) and hydrogen FC (HFC), is either produced by electrolysis (‘helec’) in modeled countries or imported

$$\sum_{\tau} l_{\tau} H_{t,\tau,r}^{EL} + IH_{t,r}^{EL} = PE_{t,r,pe|pe=\{pehgen\}} \qquad \forall\, t, \tau, r \tag{A.40}$$

Equation (A.41): Hydrogen produced by electrolysis (‘helec’) is either used in the electricity sector (EL) or in other sectors (OS).

$$S_{t,\tau,r,st|st=\{helec\}}^{OUT} = H_{t,\tau,r}^{EL} + H_{t,\tau,r}^{OS} \qquad \forall\, t, \tau, r \tag{A.41}$$

Equation (A.42): Hydrogen demand (exogenous) from other sectors (OS) is covered by electrolysis production and imports.

$$\sum_{\tau} l_{\tau} H_{t,\tau,r}^{OS} + IH_{t,r}^{OS} = h_{t,r}^{OS} \qquad \forall\, t, r \tag{A.42}$$

Equation (A.43): Minimum requirement of hydrogen produced through electrolysis within the model regions.

$$\sum_{r,\tau} l_\tau S^{OUT}_{t,\tau,r,st|st=\{helec\}} \geq \mu \sum_{r} \left(PE_{t,r,pe|pe=\{hydrogen\}} + h^{OS}_{t,r} \right) \qquad \forall\, t \qquad \text{(A.43)}$$

Equation (A.44): CO_2 emissions from electricity generation

$$E^{CO_2}_{t,r,elec} = \sum_{pe} \lambda_{pe} PE_{t,r,pe} - E^{CCS}_{t,r,elec} \qquad \forall\, t, r \qquad \text{(A.44)}$$

Equation (A.45): Captured CO_2 emissions

$$E^{CCS}_{t,r,elec} = 0.9 \sum_{pe} \lambda_{pe} \sum_{\tau} l_\tau \sum_{te \,\in\, TE^{CCS}_{pe}} {G_{t,\tau,r,te}}\Big/\big(\eta_{te}(1 - a_{te})\big) \qquad \forall\, t, r \qquad \text{(A.45)}$$

Equation (A.46): CCS storage constraint

$$\Delta t \sum_{t} E^{CCS}_{t,r,elec} \leq cap^{CCS_{cum}}_{r} \qquad \forall\, r \qquad \text{(A.46)}$$

g. Security of supply

Equation (A.47): Robustness condition

$$(1+rm)d_{t,\tau,r} \leq \sum_{te\in TE^{disp}} \left(f_{te}K_{t,r,te} + RK_{t,r,te}\right) + \sum_{st} f_{st}S^{OUT}_{t,\tau,r,st}$$
$$+ \sum_{te\in TE^{vRES}} f_{te} \sum_{rg} \alpha^{vRES}_{\tau,r,te,rg} K^{RG}_{t,r,te,rg}$$
$$+ f_{imp}\left(\sum_{cn\in CN^{in}_r} \left((1-\gamma_{cn})F^{+}_{t,\tau,cn} - F^{-}_{t,\tau,cn}\right) \right.$$
$$\left. + \sum_{cn\in CN^{out}_r} \left((1-\gamma_{cn})F^{-}_{t,\tau,cn} - F^{+}_{t,\tau,cn}\right) \right) \qquad \forall t,\tau,r \tag{A.47}$$

Equation (A.48): Reserves constraint

$$RK_{t,r,te} \leq \Delta t \sum_{tt} \left(DK_{t,tt,r,te} + 0.8DK_{t-1,tt,r,te}\right) \qquad \forall\ t,r,te \tag{A.48}$$
$$RK_{t,r,te} \leq RK_{t-1,r,te} + \Delta t \sum_{tt} DK_{t,tt,r,te} \qquad \forall\ t,r,te$$

Equation (A.49): Maximum reserves

$$\sum_{te} RK_{t,r,te} \leq \vartheta^{RK} d_{t,\tau,r} \qquad \forall\ t,\tau,r \tag{A.49}$$

h. The EU ETS

Equation (A.50): Emissions from energy-intensive industry

$$E_{t,r,s}^{CO_2} = \sum_{m} abat_{t,r,s,m}^{CO_2} - A_{t,r,s,m}^{CO_2} \qquad \forall\ t, r, s \in \{heat, industry\} \tag{A.50}$$

Equation (A.51): EUA needed by the aviation sector

$$euaa_t^{CO_2} = max\left(0, e_{t,avi}^{CO_2} - cap\_avi_t^{CO_2}\right) \qquad \forall\ t \tag{A.51}$$

Equation (A.52): EUA needed by the maritime sector

$$euam_t^{CO_2} = max\left(0, e_{t,mar}^{CO_2} - cap\_mar_t^{CO_2}\right) \qquad \forall\ t \tag{A.52}$$

Equation (A.53): Total demand of (stationary) EU allowances (EUA)

$$Emi_t^{CO_2} = \sum_{r \in R^{pol}} \sum_{s} E_{t,r,s}^{CO_2} + euaa_t^{CO_2} + euam_t^{CO_2} \qquad \forall\ t \tag{A.53}$$

Equation (A.54): Supply of certificates EUA

$$SupEUA_t^{CO_2} = cap_t^{CO_2} \qquad \forall\ t \tag{A.54}$$

Equation (A.55): Banking of EUA. The borrowing constraint is implicitly included since the TNAC variable cannot be negative.

$$TNAC_t^{CO_2} = TNAC_{t-1}^{CO_2} + \Delta t\left(SupEUA_t^{CO_2} - Emi_t^{CO_2}\right) \qquad \forall\ t \leq T^{ETS} \tag{A.55}$$

Equation (A.56): EUA trading ends in year

$$TNAC_t^{CO_2} = 0 \qquad \forall\, t > T^{ETS} \tag{A.56}$$

The Market Stability Reserve (MSR) and the carbon price floor are additional measures within the EU ETS which are described in the following. These are modules that can be switched on depending on the research aim.

h.1. The Market Stability Reserve (MSR)

Following the EU ETS reform in 2015, the MSR was created with an amendment of the Directive 2003/87/EC (European Commission, 2015). It was later also amended so as to allow EUA cancellation (European Parliament and Council of the European Union, 2018), among other changes, and started operating in 2019. Its main purpose is to deal with the growing surplus of EUA, while still ensuring the stability of the system. It is supposed to work as a safe valve, withdrawing allowances when there is surplus and releasing them when there is scarcity. The MSR has three main rules: (*i*) X certificates are transferred to the MSR instead of being auctioned when the bank size of the previous year is higher than 833 $MtCO_2$, p_intake equalling 24% (until 2023 and 12% afterwards) of the bank size; (*ii*) X certificates are transferred back from the MSR to the market when the bank size of the previous year is lower than 400 $MtCO_2$, $p\_outtake$ equalling 100 $MtCO_2$ (available through auctions); and (*iii*) when the size of the MSR stock is higher than the number of certificates to be auctioned in the previous year, the difference between both is cancelled from the MSR.

Given the non-linearity of the MSR conditions, it is not possible to embed such equations directly in LIMES-EU. Indeed, it would also be inconsistent to include the MSR in an optimization model as it violates the perfect competition assumption which we assume throughout all other parts of the model. We thus couple LIMES-EU with a simulation of the MSR, following an iterative approach, which is illustrated in Figure A1. The underlining logic is to find an emission path consistent with the bank, and thus with the total certificates available. The additional sets, parameter and variables (on an annual basis) are shown in Table A5.

Table A5. Indices, parameters and variables required to simulate the MSR.

Symbol	**Description**
	Indices
$t2$	years (annual)
	Parameters
p_cap_{t2}	EU ETS cap
p_emi_{t2}	EU ETS aggregated emissions
$p\_freeEUA_{t2}$	Free allocated allowances
$p\_prelaucEUA_{t2}$	Preliminary auction
$p\_lower\_threshold_{t2}$	Lower threshold
$p\_upper\_threshold_{t2}$	Upper threshold
$p\_rateintakeMSR_{t2}$	Intake rate to the MSR
$p\_rateoutakeMSR_{t2}$	Outtake rate from the MSR
$p\_extraintake_{t2}$	Additional intake to the MSR
$p\_sharefreeEUA_{t2}$	Share of allowances to be freely allocated
	Variables
p_TNAC_{t2}	total number of allowances in circulation in EU ETS
p_intake_{t2}	Intake of allowances into the MSR
$p\_outtake_{t2}$	Outtake of allowances from the MSR
p_MSR_{t2}	MSR level
p_aucEUA_{t2}	Allowances finally auctioned
$p\_cancellation_{t2}$	Allowances cancelled from the MSR

The cap on an annual basis (p_cap_{t2}), based on the assumed linear reduction factor (LRF), is equivalent to the cap used in LIMES-EU (cap into a 5-year value, $cap_t^{CO_2}$). More precisely,

$cap_t^{CO_2}$ averages the corresponding 5-year values to each year in LIMES-EU[21]. For instance, the cap in LIMES-EU in 2020 equals the average of the annual cap between 2018 and 2022. In a first iteration, the certificates supply ($SupEUA_t^{CO_2}$) equals the cap ($cap_t^{CO_2}$), as specified in Eq. (A.54).

From the LIMES-EU results, we use the total EUA rendered ($Emi_t^{CO_2}$) and the bank at the end of 2015 ($TNAC_{2015}^{CO_2}$) as input for the MSR. These 5-year-based inputs nonetheless have to be 'translated' into annual values for the MSR simulation. This is necessary because of the MSR operation criteria, e.g., use TNAC from year *t2-1* to estimate the intake into the MSR in *t2*, works on an annual basis. Recall that each year in LIMES-EU corresponds to the 5 years around it. To smoothen the input, we interpolate the emission volumes between LIMES-EU years and then normalize them to ensure that the 5-years average equals the LIMES-EU value. Unlike emissions, which are a flow, the TNAC in 2015 from LIMES-EU ($TNAC_{2015}^{CO_2}$) is a stock. This corresponds to the initial TNAC used in the MSR simulation, p_TNAC_{2017} (TNAC at the end of 2017). From the annual cap, we estimate the preliminary auctions ($p\_prelaucEUA_{t2}$, see Eq. (A.57)) and certificates to be freely allocated ($p\_freeEUA_{t2}$, see Eq. (A.58)).

We thus simulate the MSR operation estimating the intake (Eq. (A.59)), outtake (Eq. (A.60)), cancellation (Eq. (A.61)), MSR level (Eq. (A.62)), certificates to be auctioned (Eq. (A.63)) and TNAC (Eq. (A.64)) on an annual basis as of 2019.

$$p\_prelaucEUA_{t2} = p\_cap_{t2} \times (1 - p\_sharefreeEUA_{t2}) \tag{A.57}$$

[21] To distinguish the variables and parameters computed in LIMES-EU from those computed in the MSR simulation, we name the latter as *p_**. In addition, the index *t* is only used for input from or variables used in LIMES-EU (5-year step basis, i.e., $t = 2015, 2020 \ldots .2055$), while *t2* is only used for those related to the MSR simulation (annual basis, i.e., $t2 = 2017, 2018 \ldots .2057$).

$$p\_freeEUA_{t2} = p\_cap_{t2} \times p\_sharefreeEUA_{t2} \tag{A.58}$$

If $p\_TNAC_{t2-1} > p\_upper\_threshold_{t2}$, (A.59)

$$p\_intake_{t2} = min\left({}^{2}/_{3}\, p\_TNAC_{t2-2} \times p\_rateintakeMSR_{t2-2} + {}^{1}/_{3}\, p\_TNAC_{t2-1} \times p\_rateintakeMSR_{t2-1}, p\_prelaucEUA_{t2}\right),$$

in other case $p\_intake_{t2} = 0$

If $p\_TNAC_{t2-1} < p\_lower\_threshold_{t2}$, (A.60)

$$p\_outtake_{t2} = min(p\_MSR_{t2-1}, p\_rateouttakeMSR_{t2}),$$

in other case $p\_outtake_{t2} = 0$

$$p\_cancellation_{t2} = 0 \quad \forall t2 \leq 2023 \tag{A.61}$$

$$p\_cancellation_{t2} = max(p\_MSR_{t2-1} - p\_prelaucEUA_{t2-1}, 0)\ \forall t2 > 2024$$

$$p\_MSR_{t2} = p\_MSR_{t2-1} + p\_extraintake_{t2} + p\_intake_{t2} - p\_outtake_{t2} - p\_cancellation_{t2} \tag{A.62}$$

$$p\_aucEUA_{t2} = p\_prelaucEUA_{t2} - p\_intake_{t2} + p\_outtake_{t2} \tag{A.63}$$

$$p\_TNAC_{t2} = p\_TNAC_{t2-1} + p\_aucEUA_{t2} + p\_freeEUA_{t2} - p\_emi_{t2} \tag{A.64}$$

The intake to the MSR (Eq. (A.59)) is modelled in detail, i.e., the exact time in which allowances are removed from the auctions is considered. The European Commission informs each May about the TNAC by the end of the previous year and about the volume of certificates to be transferred to the MSR. A volume calculated on the basis of the TNAC of a year *t-1* is removed from the auctions between September in year *t* and August of year *t+1*. Since the MSR only starts absorbing certificates in January 2019, 16% of the TNAC in 2017, informed in May 2018 (1.65 $GtCO_2$), i.e., 264 $MtCO_2$, will be transfer to the MSR between January and August 2019[22]. Likewise, the TNAC at the end of 2018, informed in May 2019 (1.65 $GtCO_2$), determined the number of certificates being removed from auctions between September 2019 and August 2020[23] and transferred to the MSR. Accordingly, it can be assumed that the intake for each year *t* amounts to two thirds of the volume calculated on the basis of the TNAC by the end of *t-2* and one third of the volume calculated on the basis of the TNAC by the end of the year *t-1*, such volume depending on the intake rate.

[22] Communication from the Commission C(2018) 2801 final, available at https://ec.europa.eu/clima/sites/clima/files/ets/reform/docs/c_2018_2801_en.pdf

[23] Communication from the Commission C(2019) 3288 final, available at https://ec.europa.eu/clima/sites/clima/files/ets/reform/docs/c_2019_3288_en.pdf

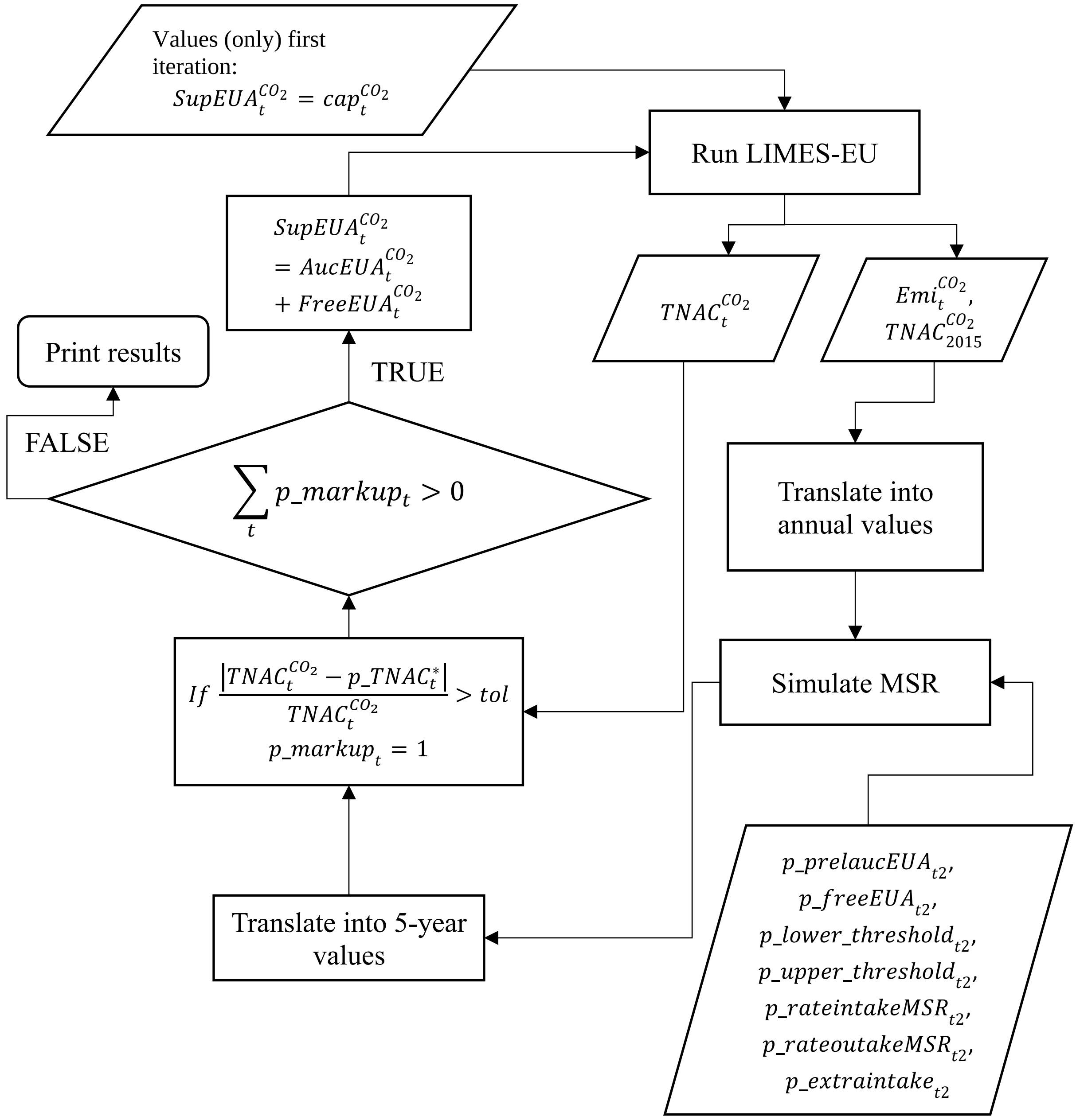

Figure A1. Iterative process to couple LIMES-EU with the MSR simulation.

This output is ‘translated’ into 5-year data. For flow-type variables we compute the average for the 5-corresponding years. For instance, the average EUA auctioned (p_aucEUA_{t2}) between 2018 and 2022 is used for the 2020 volume in LIMES-EU ($AucEUA_{2020}^{CO_2}$). For stock-type variables, p_TNAC_{t2} and p_MSR_{t2}, we use the value from the last corresponding year. For instance, their level in 2022 would correspond to 2020 in LIMES-EU years. We compute the error between the 'translated' TNAC from the MSR simulation ($p\_TNAC_t^*$) and that from LIMES-EU ($TNAC_t^{CO_2}$). If the error is higher than the tolerance margin ($tol = 0.05$) for any *t*, LIMES-EU is run again with an updated supply of certificates ($SupEUA_t^{CO_2}$), recalculating Eq. *(A.54)*. This equals the sum between the 'translated' free allocated EUA ($FreeEUA_t^{CO_2}$, based on $p\_freeEUA_{t2}$), which does not change across iterations, and the 'translated' final auctioned EUA ($AucEUA_t^{CO_2}$, based on p_aucEUA_{t2}), estimated through the MSR simulation. This process is followed until the TNAC from both LIMES-EU and the MSR simulation converge.

h.2. Myopia representation

Different publications suggest that compliance actors on the EU ETS behave myopically (Bocklet and Hintermayer, 2020; Flachsland et al., 2019; Quemin, 2020; Quemin and Trotignon, 2019; Willner, 2018): many firms might not consider the long-term future but rely on short-term planning horizons of e.g., 5-10 years (Ottmar Edenhofer et al., 2019). To simulate the effect of myopic behavior of decision-makers, we extend LIMES-EU by the option to use rolling time horizons instead of full intertemporal foresight. Mathematically this means that instead of solving one optimization problem over the whole time period from 2010 until 2070, multiple optimization problems, covering shorter time periods are solved consecutively (Figure A2). The length of the foresight horizon can be varied. As the default option, we choose 10-year horizons with an overlap of 5 years between the horizons. Practically it means, actors have foresight of 10 years but can revise their decisions every 5 years. As LIMES-EU runs in five-year time steps, one optimization horizon then comprises two-time steps (e.g., [2020, 2025], covering years 2018 - 2027).

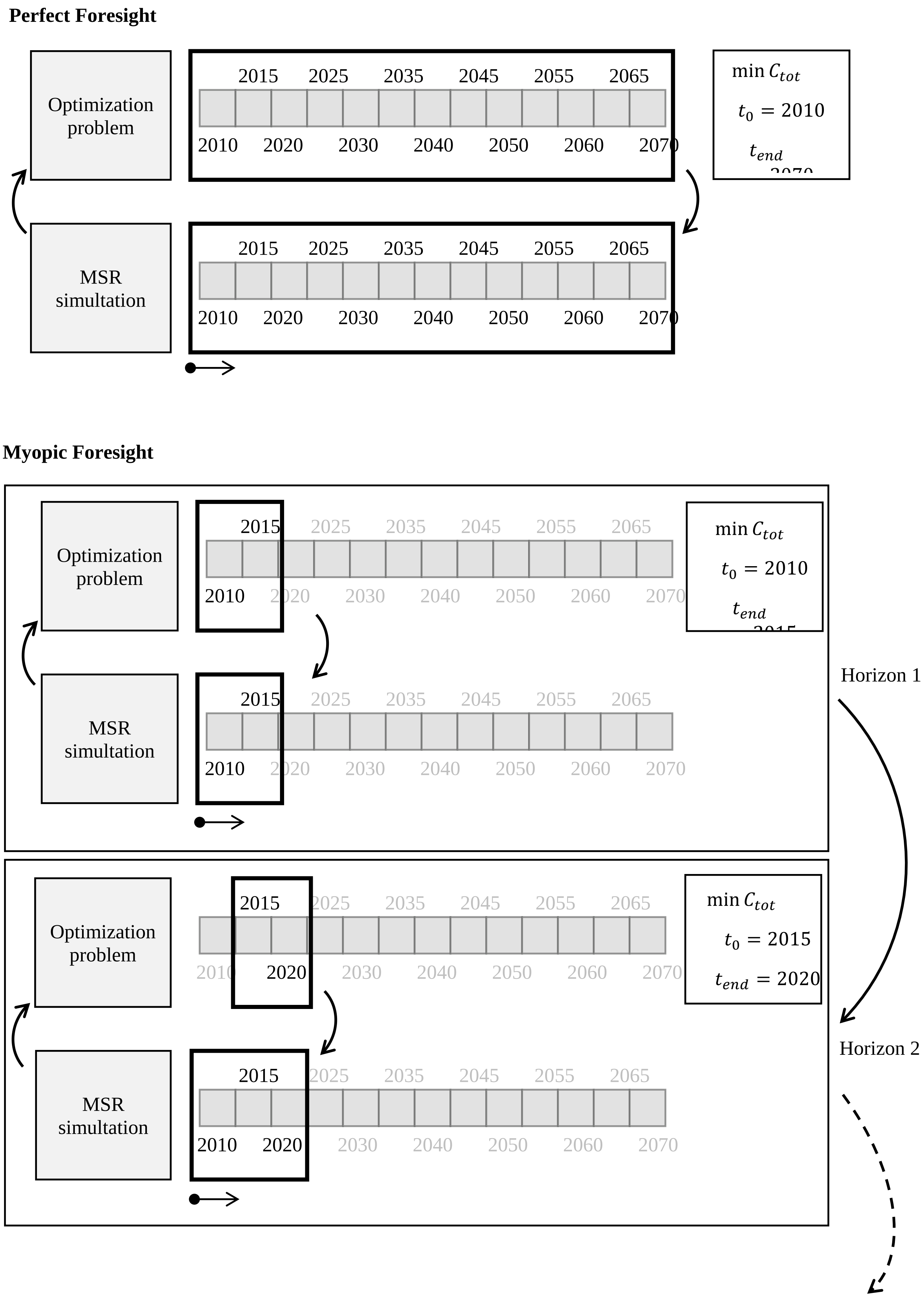

Figure A2. Interaction with the MSR loop in perfect and myopic foresight

When running in myopic foresight, several variable values such as capacity investments computed in one optimization horizon need to be fixed at the beginning of the next optimization horizon. E.g., for the optimization horizon [2020, 2025] several variable values will be fixed for 2020 and all-time steps before 2020. Dispatch decisions can still get revised every time step (5 years), so e.g., for the optimization horizon [2020, 2025], dispatch-related values get fixed only for all time steps before 2020, but not 2020 itself. The MSR, which is originally implemented iteratively as a loop around the main optimization problem, runs in the myopic model version around each time horizon (Figure A2).

Our modelling approach implies that actors don't consider any information outside of their 10 years foresight horizon (i.e., future cap or estimated future technology prices). Nonetheless, to allow for long-term investments, same as in the perfect foresight LIMES-EU version, a salvage value for the capacity stock remaining at the end the optimization horizon is subtracted from the cost function. In the myopic version, the salvage value is considered in each time horizon.

i. Other electricity sector policies

Equation (A.65): CO_2 emission target for a group of regions

$$\sum_{r \in R^{pol}} E_{t,r,elec}^{CO_2} \leq cap_t^{CO_2} \qquad \forall\, t \tag{A.65}$$

Equation (A.66): CO_2 emission target for a single region

$$E_{t,r,elec}^{CO_2} \leq cap_{t,r}^{CO_2} \qquad \forall\, t, r \tag{A.66}$$

Equation (A.67): CO_2 budget for a group of regions

$$\Delta t \sum_{t} \sum_{r \in R^{pol}} E_{t,r,elec}^{CO_2} \leq bud^{CO_2} \tag{A.67}$$

Equation (A.68): CO_2 budget for a single region

$$\Delta t \sum_{t} E_{t,r,elec}^{CO_2} \leq bud_r^{CO_2} \qquad \forall\, r \tag{A.68}$$

Equation (A.69): National RES target

$$\sum_{\tau} l_\tau \sum_{te\, \in TE^{RES}} G_{t,\tau,r,te} \geq res_{t,r} \qquad \forall\, t,r \tag{A.69}$$

Equation (A.70): Target on minimum amount of electricity provided domestically

$$\sum_{\tau} l_\tau \sum_{te\, \in TE^{RES}} G_{t,\tau,r,te} \geq \phi_r \sum_{\tau} l_\tau d_{t,\tau,r} \qquad \forall\, t,r \tag{A.70}$$

j. Steel sector module

Equation (A.71): Scrap availability for a group of countries for which demand is met

$$\sum_{ti^{steel}} \sum_{r \in R^{pol}} \beta_{ti,scrap} Q_{t,r,ti}^{steel} \leq ScrapAvail_t \qquad \forall\, t \tag{A.71}$$

Equation (A.72) and (A.73): Refurbishment only allowed when decommissioned capacity exists, ensuring that plants can be extended indefinitely as long as there is prior full investment

$$\Delta K^{steel}_{t,r,BF-BOF-relined} \leq \sum_{(t,tt)|(tt+\psi_{BF.BOF-new}\leq t)} DK^{steel}_{t,tt,r,BF.BOF-new} + \sum_{(t,tt)|(tt+\psi_{BF.BOF-relined}\leq t)} DK^{steel}_{t,tt,r,BF.BOF-relined} \quad \forall\, t,r \tag{A.72}$$

$$\Delta K^{steel}_{t,r,EAF-refurb} \leq \sum_{(t,tt)|(tt+\psi_{EAF-new}\leq t)} DK^{steel}_{t,tt,r,EAF-new} + \sum_{(t,tt)|(tt+\psi_{EAF-refurb}\leq t)} DK^{steel}_{t,tt,r,EAF-refurb} \quad \forall\, t,r \tag{A.73}$$

Equation (A.74): For DRI-EAF, we allow flexible switching between gas and hydrogen variants when replacing existing capacity

$$\sum_{ti\in TI^{steel}_{ref}\cap TI^{steel}_{DRI-EAF}} \Delta K^{steel}_{t,r,ti} \leq \sum_{ti\in TI^{steel}_{DRI-EAF}} \sum_{(t,tt)|(tt+\psi_{ti}\leq t)} DK^{steel}_{t,tt,r,BF.BOF-new} \quad \forall\, t,r \tag{A.74}$$

Equation (A.75): To reflect engineering and market constraints, we cap new capacity additions in each country

$$\sum_{ti\in TI^{steel}_{new}} \Delta K^{steel}_{t,r,ti} \leq \kappa^{steel} \quad \forall\, t,r \tag{A.75}$$

B. Region Codes

The region codes in this documentation are based on standard ISO 3166-1.

Table A6. Region codes.

Region code	Region name
AT	Austria
BE	Belgium
BG	Bulgaria
CZ	Czech Republic
DE	Germany
DK	Denmark
EE	Estonia
ES	Spain
FI	Finland
FR	France
GB	United Kingdom
GR	Greece
HR	Croatia
HU	Hungary
IE	Ireland
IT	Italy
LT	Lithuania
LU	Luxemburg
LV	Latvia
NL	The Netherlands
PL	Poland
PT	Portugal
RO	Romania
SE	Sweden
SI	Slovenia
SK	Slovakia
Balkan	Albania, Bosnia and Herzegovina, Kosovo, Montenegro, The former Yugoslav Republic of Macedonia, Serbia
CH	Switzerland
NO	Norway