# 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 analyzing comprehensive scenarios on the cost-effective future development of the European power system and the European Union's Emission Trading System (EU ETS). 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 |

Contents

# 1. Introduction

The Paris Agreement demands strong actions to decarbonize the electricity systems. In Europe several policies are in place with the aim 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. This paper introduces a techno-economic model suitable to analyze such questions called The **L**ong-term **I**nvestment **M**odel for the **E**lectricity **S**ector of **EU**rope (LIMES-EU).

Within the framework of the European Green Deal, the European Union (EU) has a goal of net-zero greenhouse gas (GHG) emissions by 2050. In addition, the 2030 GHG emissions must be reduced by at least 55% compared to 1990 levels.[2] These targets have to be translated into specific measures for the two systems covering all the economic activities, i.e., the Effort Sharing Decision (ESD) and the EU ETS. LIMES-EU models the electricity sector in detail as well as the energy-intensive industry and district heating, which are covered by the EU ETS. The EU has recently tightened the EU ETS cap as part of the 'Fit for 55' package increasing the overall ambition of emissions reductions by 2030 to 62%.[3] Such measures certainly have a strong impact on the power sector which can be analyzed with LIMES-EU.

The core assets of the power sector - electricity generation, storage and transmission technologies - are characterized by long technical lifetimes that span over several decades. Long-term planning by relevant actors such as policy makers, transmission system operators and electricity producers is therefore pivotal. In order to support policy makers in identifying

[2] 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')

[3] 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)

robust policy targets long-term scenarios are needed to explore possible pathways for the European electricity sector that are technically feasible and economically sensible.

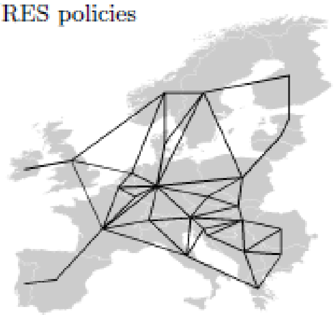
LIMES-EU was developed to facilitate a long-term assessment of the European power system on aggregate and national level. Incorporating electricity generation, storage and transmission technologies LIMES-EU simultaneously optimizes investment decisions in 5-year steps from 2010 to 2070 for each country 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. In this way LIMES-EU delivers consistent and cost-effective scenarios for the future European power system.

LIMES-EU is especially useful to analyze the integration of variable renewable energy sources (vRES) such as wind and solar into the European power system while considering flexibility operational constraints. Despite its long-term focus it accounts for short-term fluctuations of demand and vRES supply when determining the optimal electricity generation mix. Its comprehensive approach to simultaneously optimize investments in generation and storage technologies as well as cross-border transmission capacities allows for a sound technological and economic analysis of vRES integration options. Although the core of the model is the power sector, LIMES-EU also incorporates a rough representation of the energy-intensive industry such that the EU ETS as a whole can be analyzed. See Figure 1 for a summary of the model features.

**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.*

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. In order 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.

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 and 5 discuss the standard parameter assumptions used to run the model, with Section 4 focusing on technology-specific parameters that are same for every model region and Section 5 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 7. Sections 8 and 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 $\Delta t$ 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 $\rho$ which is set to 5% in the standard case. 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 exogenous to the model. 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[4] and uses the linear solver CPLEX.

## 2.2. Geographical Resolution

The current version of LIMES-EU optimizes the electricity system and abatement of the energy-intensive industry of the EU countries (excluding Cyprus and Malta) plus the Balkan region, Norway, Switzerland and the United Kingdom. Except for the Balkan region, all countries are modeled as individual entities. They differ with respect to 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

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

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

In order to accommodate both long-term investment decisions and short-term fluctuations of wind, solar irradiance and demand, 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 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 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 modeled 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 three kinds of technologies represented in LIMES-EU, namely generation, storage and transmission technologies. Section 3 provides a more detailed description of each technology. Power plants, transmission lines and storage facilities are not represented on a single unit basis in LIMES-EU, but are aggregated based on their economic and technical characteristics[5]. Modelling technology classes rather than individual units considerably simplifies the model, which otherwise could not be solved due to computational constraints.

**Generation Technologies** Generation technologies 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 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

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

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 neighboring regions. Transmission is modelled as a transport problem from the center of one region to the center of a neighboring 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.

## 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 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 is applicable 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 fulfill 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 with respect to 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.

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[6] are much higher than the ones derived from the weather data. The spatial resolution of 0.75° ×

[6] Spain in particular but also Austria and Italy.

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:

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

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

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[7]. 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 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 5.1 and 7).

[7] the distribution of elevation within a grid cell is based on NGDC (2013).

## 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[8] per observation. Before starting the clustering algorithm all-time 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.

[8] 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.

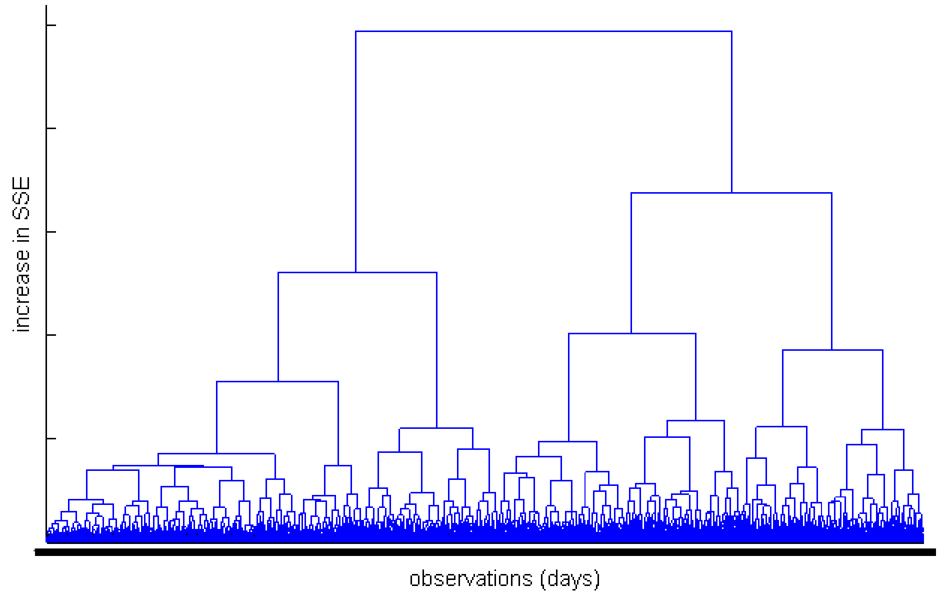



*Figure 2. Dendrogram of clustering procedure. Showing the consecutive grouping of two clusters to a joint cluster and the resulting increase in the overall sum of squared errors (SSE, y-axis). All days (x-axis) are consecutively grouped together until only one cluster is left. Source: Own computation 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) analyze 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. However, more days are needed for vRES and storage deployment to converge (see Section 9). We therefore use a number of representative days according to the aim of the study/research, e.g., 6 days (i.e., 48 time slices) would be appropriate for studies focused on the EU ETS as these are enough to capture long-term emission patterns, and 8-10 days for studies focused on long-term investments in the power sector.

# 4. Technology Characteristics

## 4.1. Generation Technologies

### 4.1.1. 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 2 presents the investment cost assumptions for our default scenario, which are based on REMIND[9].

*Table 1. Characteristics of wind and solar power plants.*

| | Fixed O&M (%/a) | Lifetime (a) |
|---|---|---|
| Wind Onshore | 3 | 25 |
| Wind Offshore | 3 | 25 |
| PV | 1 | 30 |
| CSP | 3 | 30 |

Source: Haller *et al.* (2012) and own assumptions.

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

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

| | Wind Onshore | Wind Offshore | PV | CSP |
|---|---|---|---|---|
| 2010 | 1764 | 4750 | 2500 | 6250 |
| 2015 | 1605 | 4412 | 1100 | 5100 |
| 2020 | 1257 | 2736 | 703 | 4750 |
| 2025 | 1197 | 2419 | 488 | 4750 |
| 2030 | 1137 | 2102 | 395 | 4750 |
| 2035 | 1062 | 2000 | 357 | 4600 |
| 2040 | 987 | 1900 | 340 | 4450 |
| 2045 | 955 | 1800 | 332 | 4000 |
| 2050-2070 | 923 | 1700 | 326 | 3560 |

Source: IEA (2019), IEA PVPS (2021); REMIND data and own assumptions.

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[10] $cap_i$ (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

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

speed[11]. The resulting wind power curve which is defined by the five coefficients $\beta_{1-5}$ 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.

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

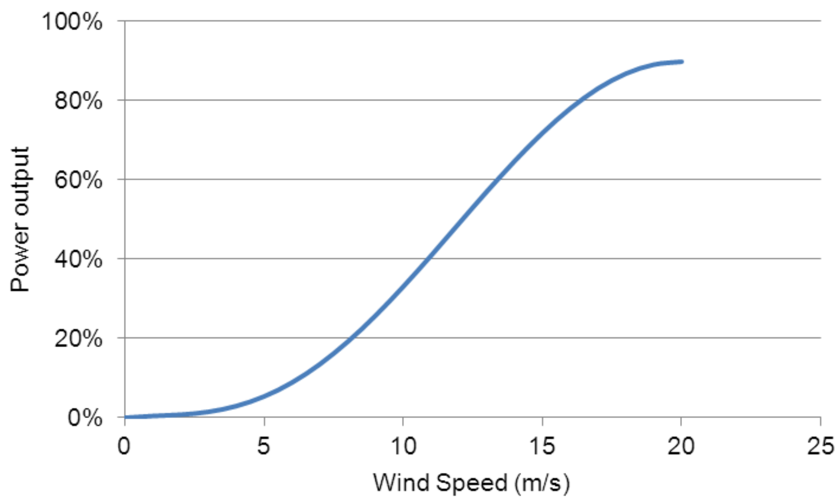



*Figure 3. Aggregated wind power curve. Source: Own calculations based on Dee et al. (2011), ÜNB (2013a) and ÜNB (2013b).*

[11] 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, $\rho$ 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 $v$.

As in Haller *et al.* (2012), CSP plants are modelled with an collector area that is four times the size required to reach nominal output at reference conditions (SM4[12] configuration). Each CSP plant is equipped with an 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.

### 4.1.2. Dispatchable Generation Technologies

Power plants using fossil fuels, uranium, biomass or hydro power as a primary energy source are dispatchable within the limits of their annual availability. Except for hydro[13], the annual availability of these technologies is equal for all model regions (80%). Hourly availability for all technologies is defined as 100% minus the auto consumption rate (from Agora (2014)). Table 3 gives an overview about the techno-economic characteristics of fuel- and hydro-based power plants in LIMES-EU. 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.

*Table 3. Techno-economic characteristics of thermal and hydro power 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.*

| | Investment Costs (€/kW) | Efficiency (%) | Autocons. (%) | Fixed O&M (%/yr) | Variable O&M (e/MWh) | Min Load (%) | Max Ramp (%) | Lifetime (yr) |
|---|---|---|---|---|---|---|---|---|
| Nuclear | 7000 | 33 | 5 | 3 | 5 | 40 | - | 60 |
| Hard Coal | 1800 | 38-50 | 8 | 2 | 6 | 30 | 35 | 45 |
| Hard Coal CCS | see Table 4 | 45 | 8 | 2 | 29 | 30 | 35 | 45 |
| Lignite | 2100 | 36-47 | 8 | 2 | 9 | 50 | 25 | 55 |

[12] SM: solar multiple.
[13] See Section 5.3.2.

| | Investment Costs (€/kW) | Efficiency (%) | Autocons. (%) | Fixed O&M (%/yr) | Variable O&M (e/MWh) | Min Load (%) | Max Ramp (%) | Lifetime (yr) |
|---|---|---|---|---|---|---|---|---|
| Lignite CCS | see Table 4 | 42 | 8 | 2 | 34 | 50 | 25 | 55 |
| Gas CC | 900 | 54-60 | 3 | 3 | 4 | 40 | 50 | 45 |
| Gas CC CCS | see Table 4 | 52 | 3 | 3 | 18 | 40 | 50 | 45 |
| Gas GT | 468 | 41 | 3 | 3 | 3 | 0 | 100 | 45 |
| Oil | 390 | 42 | 9 | 4 | 3 | 0 | 100 | 40 |
| Hydrogen CC | 945 | 57 | 3 | 3 | 4 | 0 | 100 | 40 |
| Hydrogen CT | 491 | 39 | 3 | 4 | 3 | 0 | 100 | 40 |
| Hydrogen FC | see Table 4 | 45 | 3 | 2 | 3 | 0 | 100 | 40 |
| Waste | 2000 | 22 | 2 | 4 | 3 | 0 | 35 | 40 |
| Other gases | 900 | 76 | 8 | 3 | 3 | 40 | 50 | 40 |
| Biomass | 2000 | 42 | 5 | 4 | 6 | 0 | 35 | 40 |
| BECCS | see Table 4 | 42 | 30 | 2 | 6 | 0 | 35 | 40 |
| Hydro | 2500 | 100 | 2 | 2 | 0 | 0 | 100 | 80 |

Source: Agora (2014), BMWi (2018), Capros *et al.* (2018), Danish Energy Agency and Energinet (2020), Markewitz *et al.* (2018), UBA (2018); own assumptions.

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

| | Hard Coal CCS | Lignite CCS | Gas CC CCS | Hydrogen FC | BECCS |
|---|---|---|---|---|---|
| 2010 | 3748 | 3748 | 2113 | 2000 | 3800 |
| 2015 | 3748 | 3748 | 2113 | 1800 | 3800 |
| 2020 | 3475 | 3475 | 1942 | 1600 | 3800 |
| 2025 | 3200 | 3200 | 1800 | 1400 | 3625 |
| 2030 | 3000 | 3000 | 1700 | 1200 | 3450 |
| 2035 | 2900 | 2900 | 1600 | 1000 | 3270 |
| 2040 | 2800 | 2800 | 1550 | 900 | 3090 |
| 2045 | 2700 | 2700 | 1500 | 800 | 3045 |
| 2050-2070 | 2600 | 2600 | 1450 | 700 | 3000 |

Source: Capros *et al.* (2018); REMIND data and own assumptions.

Power plants with steam turbines are subject to minimum load restrictions and ramping constraints. In order to represent these characteristics, the dispatch is limited via two equations: first, the model choses 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 constraining the variation in generation 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[14] (see Table 5); as part of the calibration process we add cost markups for lignite, gas and hard coal for certain model regions. However, the availability of certain fuels, namely lignite and biomass, differs between model regions (see Section 5.3.2).

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 the BMWi (2018) and are considered equal for every model region for simplicity and due to the lack of sufficient data. In reality, the emission intensity of lignite significantly depends on the site of extraction and differs not only between but also within regions. The emission factors for all the fuels in the model fall nonetheless within the ranges provided by the IPCC (Gomez et al., 2006).

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

The only 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 (Fajardy and Dowell, 2017). For instance, according to Fajardy and Dowell (2017)'s estimations, 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. It is clear that the supply chain emissions cannot be entirely accounted because some of these emissions are already covered by the EU ETS or ESD (e.g., transport of biomass, included in the ESD). However, unlike other primary energies, harvesting biomass directly affects the absorption of CO2, and thus the countries' emission inventories. Hence, land use change (LUC) and indirect land use change (ILUC) should be accounted. Based on a 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%[15], 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.

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

| | Fuel prices (€/GJ) | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2010 | 2015 | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 | 2050 | 2055 | 2060 | 2065 | 2070 |
| Hard Coal | 2.9 | 2.3 | 3.0 | 3.0 | 3.0 | 3.1 | 3.2 | 3.4 | 3.6 | 3.6 | 3.6 | 3.6 | 3.6 |
| Lignite | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 |
| Natural Gas | 5.7 | 5.3 | 6.2 | 6.8 | 7.1 | 7.8 | 8.3 | 8.4 | 8.9 | 8.9 | 8.9 | 8.9 | 8.9 |
| Uranium | 0.5 | 0.6 | 0.7 | 0.8 | 1.0 | 1.2 | 1.4 | 1.7 | 2.0 | 2.0 | 2.0 | 2.0 | 2.0 |
| Biomass | 5.9 | 5.9 | 6.0 | 6.0 | 6.0 | 8.0 | 12.0 | 16.0 | 20.0 | 23.0 | 25.0 | 26.0 | 28.0 |
| Oil | 10.7 | 8.0 | 11.9 | 13.2 | 14.3 | 16.4 | 16.0 | 17.6 | 19.3 | 19.3 | 19.3 | 19.3 | 19.3 |
| Waste | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| Hydrogen | 12.5 | 12.5 | 13.9 | 13.9 | 13.9 | 13.9 | 13.9 | 13.9 | 13.9 | 13.9 | 13.9 | 13.9 | 13.9 |

[15] 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.

| | Fuel prices (€/GJ) | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2010 | 2015 | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 | 2050 | 2055 | 2060 | 2065 | 2070 |
| Other gases | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |

Source: fuel prices taken from respective REMIND runs, Strefler et al. (2021); own assumptions.

*Table 6. Emission factors.*

| | $CO_2$ intensity | |
|---|---|---|
| | $tCO_2/TJ$ | $tCO_2/kWh_{th}$ |
| 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: BMWi (2018) and Gomez et al. (2006); own assumptions.

## 4.2. 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 investments 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 | 1129 | 80 | 1 | 0 | 80 | 80 |
| Batteries | see Table 8 | see Table 8 | 1 | 0 | 80 | 20 |
| Hydrogen electrolysis | see Table 8 | 0.1 | 2 | 3 | 70 | 20 |

Source: Schmidt et al. (2019), Reuß et al. (2017), and own assumptions.

*Table 8. Storage technologies with time-dependent investment costs. Investments 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) | 678 | 678 | 373 | 231 | 156 | 122 | 108 | 102 | 95 |
| | Storage (€/kWh) | 802 | 802 | 441 | 273 | 184 | 144 | 128 | 120 | 112 |
| Hydrogen Electrolysis | Power (€/kW) | 1595 | 1595 | 1282 | 973 | 662 | 629 | 596 | 563 | 530 |

Source: Schmidt et al. (2019), Saba et al. (2018) 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 corresponding investment needs of electrolysis. Instead, we implement a proxy for electrolysis storage capacity (hydrogen storage capacity). We assume an exogenous number of cycles (equal to 1 in the reference scenario), 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.

## 4.3. 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 neighboring 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 and thereby increasing the NTC between two countries. Investment costs depend on the additional capacity to be installed and the distance between the two country-centers. Table 9 summarizes the techno-economic characteristics of NTCs applied in the model.

The specific NTC investment cost vary significantly in the literature: Instead of the 1M€/GWkm in Hirth (2013) and LIMES-EU, Schaber *et al.* (2012) and Fürsch *et al.* (2013) only assume costs of 0.4 M€/GWkm. However, 0.4M€/GWkm rather reflect the costs for thermal transfer capacity than for NTC: NEP (2013) state costs of 1.4 M€/km for a 380kV overhead double-circuit. With a transfer capacity of about 1.8 GW per circuit, this results in 0.4 M€ per GWkm of thermal capacity (cf. DENA (2010), IZES *et al.* (2011)). There are several reasons, why we assume the costs per NTC to be much higher: (1) NTC values are significantly smaller than thermal transfer capacities; (2) the stated costs only cover the lines and do not comprise substations and converters; and (3) costs for underground and sea cables are considerably higher than for overhead lines. We therefore assume that 1M€ per GWkm NTC is an appropriate approximation of the real transmission investment costs.

*Table 9. Characteristics of transmission technologies.*

| | Inv. Costs (M€/GWkm) | Availability (%) | Lifetime (yr) | Losses (%/1000km) |
|---|---|---|---|---|
| Net Transfer Capacity (NTC) | 1.0 | 80 | 100 | 7 |

Source: Haller *et al.* (2012), Short *et al.* (2011), NEP (2013); own assumptions.

## 4.4. 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 $\psi_{te}$ 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.

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

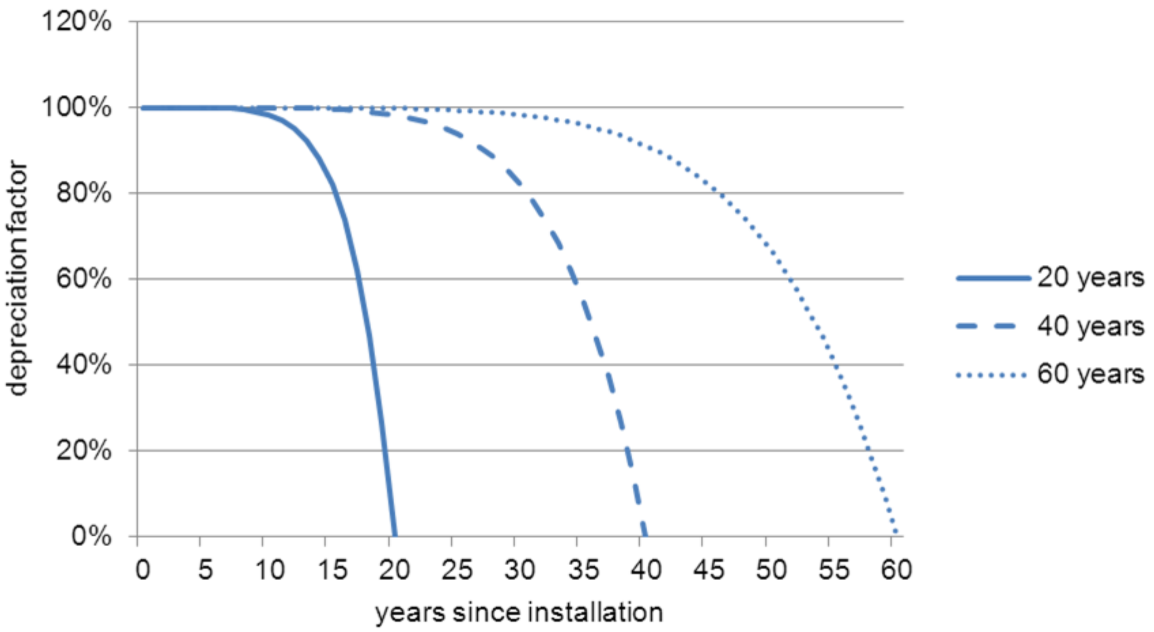



*Figure 4. Depreciation factor ω for three different technological lifetimes (20, 40, 60 years).*

## 4.5. 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 10 shows the assumed derating factors and the variables that they multiply in order 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 g.

*Table 10. 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.

# 5. Region-Specific Input Data

## 5.1. Electricity Demand

### 5.1.1. Annual demand

As discussed in Section 3, the intra-year variation of the model regions' electricity consumption is based on ENTSO-E (2016). Final annual electricity consumption for 2010 and 2015 is retrieved from EUROSTAT (2018a) for all countries except Switzerland, for which BFE (2017) statistics are used. Demand projections until 2050 are based on European Commission (2016) for EU members and BFE (2013) for Switzerland for default scenarios. Future demand for Norway and Balkan countries is estimated based on the growth rates of their neighboring countries for which data is available. To account for the most recent estimations regarding sector coupling due, mainly, to larger electrification of heating and transportation, we scale 2020-2050 demand using the data (at EU level, data at national-level not available) from the EU's "strategic long-term vision for a prosperous, modern, competitive and climate-neutral economy by 2050" (European Commission, 2018). For years after 2050 until 2070 we assume that the demand is fixed at 2050 values.

Table 11 reports both the historical data for 2010 and 2015, and the default projections for future electricity demand. Regarding the year 2050, electricity consumption is projected to rise in every model region. However, the relative increase differs strongly across countries, with Switzerland (+4%) and Luxembourg (+94%) being at the lower and upper end, respectively. An explanation of the region codes used in this document is given in Appendix B. Based on historical data, it is assumed that the required production of electricity has to exceed the reported final electricity consumption by 8% to account for intra-regional transmission and distribution losses.

Table 11. Default assumptions for final electricity demand (in TWh).

| Region | 2010 | 2015 | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 | 2050-2070 |
|---|---|---|---|---|---|---|---|---|---|
| BE | 86.3 | 83.1 | 84.7 | 88.3 | 93.9 | 98.7 | 105.4 | 114.7 | 124.2 |
| BG | 28.3 | 29.6 | 29.3 | 31.2 | 32.8 | 34.0 | 35.5 | 37.9 | 40.9 |
| CZ | 56.2 | 56.4 | 61.5 | 66.3 | 69.8 | 74.0 | 77.8 | 84.4 | 90.9 |
| DK | 33.0 | 31.7 | 33.1 | 35.7 | 37.7 | 40.6 | 43.1 | 47.0 | 51.1 |
| DE | 546.9 | 528.4 | 534.7 | 563.9 | 590.0 | 603.4 | 613.4 | 639.1 | 666.3 |
| EE | 7.4 | 7.4 | 7.7 | 8.1 | 8.8 | 9.2 | 9.6 | 10.5 | 11.3 |
| IE | 25.6 | 25.9 | 26.4 | 28.2 | 29.7 | 31.5 | 33.2 | 35.8 | 39.0 |
| GR | 55.3 | 52.4 | 53.7 | 53.8 | 53.3 | 56.8 | 58.8 | 61.5 | 64.8 |
| ES | 250.2 | 238.5 | 248.6 | 257.8 | 270.9 | 282.7 | 292.9 | 311.3 | 334.3 |
| FR | 471.8 | 443.0 | 455.9 | 473.7 | 495.3 | 525.3 | 550.9 | 587.6 | 629.1 |
| HR | 16.2 | 15.7 | 16.3 | 16.8 | 17.3 | 18.4 | 19.4 | 21.3 | 23.6 |
| IT | 309.9 | 297.2 | 306.8 | 316.8 | 331.1 | 360.7 | 389.2 | 420.8 | 453.8 |
| LV | 6.2 | 6.5 | 7.3 | 7.9 | 8.5 | 9.0 | 9.8 | 10.6 | 11.4 |
| LT | 9.3 | 10.2 | 10.4 | 10.8 | 10.8 | 11.1 | 11.4 | 12.5 | 13.4 |
| LU | 6.6 | 6.2 | 7.0 | 7.8 | 8.8 | 10.0 | 11.3 | 12.6 | 13.8 |
| HU | 36.0 | 37.4 | 36.2 | 39.5 | 41.3 | 43.6 | 46.5 | 50.8 | 54.2 |
| NL | 112.3 | 109.8 | 111.4 | 118.3 | 122.7 | 127.4 | 133.4 | 142.1 | 152.6 |
| AT | 62.2 | 63.6 | 67.8 | 72.1 | 76.5 | 80.2 | 84.2 | 90.3 | 95.1 |
| PL | 129.4 | 138.9 | 143.2 | 161.3 | 177.6 | 190.2 | 201.4 | 216.8 | 232.5 |
| PT | 50.6 | 46.8 | 47.5 | 49.3 | 50.4 | 52.0 | 53.7 | 56.3 | 58.6 |
| RO | 46.0 | 46.8 | 47.6 | 50.9 | 53.9 | 57.2 | 61.0 | 66.2 | 71.6 |
| SI | 12.1 | 12.9 | 13.6 | 15.2 | 15.9 | 16.5 | 17.3 | 18.5 | 19.8 |
| SK | 25.1 | 25.4 | 27.3 | 30.4 | 32.8 | 34.6 | 35.8 | 37.6 | 39.3 |
| FI | 84.8 | 79.7 | 80.4 | 85.2 | 88.5 | 92.7 | 96.2 | 103.1 | 110.4 |
| SE | 135.0 | 127.8 | 136.6 | 144.3 | 152.2 | 159.1 | 165.3 | 177.9 | 190.5 |
| GB | 337.5 | 311.0 | 325.0 | 341.4 | 359.4 | 381.6 | 414.5 | 450.3 | 471.5 |
| NO | 119.3 | 118.6 | 124.9 | 128.2 | 131.5 | 134.8 | 138.1 | 141.5 | 144.8 |
| CH | 59.8 | 58.2 | 55.7 | 57.2 | 57.9 | 59.6 | 61.5 | 62.9 | 63.2 |
| Balkan | 55.2 | 55.1 | 53.7 | 55.0 | 55.6 | 57.8 | 60.4 | 63.0 | 65.5 |

Source: European Commission (2018, 2016), EUROSTAT (2018a), BFE (2013), BFE (2017); own assumptions.

### 5.1.2. Hourly patterns

As explained in Section 3.2, we use a clustering algorithm to derive the hourly demand. These nonetheless follow the patterns from original data (2010-2011). Although demand is scaled using annual demand, the changes in peak demand in certain countries in the last decade are larger than changes in annual demand. For instance, peak demand in GB decreased from 61 GW in 2010 to (expectedly) 48 GW in 2020 (ENTSO-E, 2019a) (see Table 12), i.e., 21%. In the same period, annual demand only decreased from 329 to 325 TWh (i.e., 1%). To account for changes in such patterns over time, we rescale hourly demand 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 12. Peak demand in 2010 and 2020.*

| Region | 2010 | 2020 | Region | 2010 | 2020 | Region | 2010 | 2020 |
|---|---|---|---|---|---|---|---|---|
| FI | 14.6 | 13.4 | PL | 19.5 | 25.1 | SI | 1.9 | 2.4 |
| NO | 20.7 | 21.9 | DE | 84.7 | 79.9 | FR | 88.6 | 82.2 |
| SE | 24.8 | 26.7 | BE | 14.0 | 13.2 | HR | 2.8 | 2.9 |
| EE | 1.3 | 1.4 | LU | 1.0 | 1.0 | BG | 4.9 | 6.3 |
| LV | 1.1 | 1.2 | CZ | 9.6 | 10.6 | IT | 51.9 | 51.6 |
| LT | 1.4 | 2.1 | SK | 3.9 | 4.6 | ES | 38.9 | 39.5 |
| DK | 6.0 | 6.0 | AT | 10.1 | 11.5 | PT | 8.8 | 7.3 |
| GB | 60.6 | 48.1 | CH | 9.7 | 10.3 | GR | 8.8 | 8.0 |
| IE | 4.5 | 5.3 | HU | 5.6 | 6.3 | Balkan | 10.6 | 12.2 |
| NL | 18.1 | 18.2 | RO | 6.8 | 9.3 | | | |

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

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

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

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

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

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

$$dem\_nonadj_{\tau,r} = d_{2020,\tau,r} + deltadem_r \qquad (8)$$

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

$$demscale\_adj_{\tau,r} = dem\_nonadj_{\tau,r} * 8760 \big/ \sum_\tau dem\_nonadj_{\tau,r} l_\tau \qquad (9)$$

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

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

## 5.2. Installed Capacities in 2015 and 2020

### 5.2.1. Generation

As the model is calibrated to 2015 as base year, installed capacities in 2015 are set exogenously. The existing capacities of generation and storage technologies (see Table 13) are derived from Open Power System Data (2018), which aggregates data from different official sources, e.g., ENTSO-E, local TSOs and local ministries. For instance, in the specific case of Germany, data from the BMWi (2018) is used. The age structure of technologies is derived from Platts (2011) and EUROSTAT (2018b). Due to lack of reliable data for the rest of countries, waste and other gases capacities are only considered in Germany.

We also fix or bound the capacities for 2020 (see Table 14), but due to the lack of data we keep the full calibration to 2015 data. We assume conventional technologies to vary ±5% from 2019 capacities, while vRES are fixed to estimate capacities. Due to lack of data we assume biomass capacity cannot grow more than 20% in 2020 with respect to its level in 2015. In addition, we assume the share of CCG and GT gas plants of 2015 remains in 2020; biomass capacity cannot grow more than 20% with respect to its level in 2015; and CSP corresponds to the one installed by 2018. We use public sources in our estimations: dispatchable technologies and PSP capacities are derived from the Winter Outlook 2019/2020 (ENTSO-E, 2019a); vRES capacities are interpolated between the current capacities (IRENA, 2018) and the expected capacities from WindEurope (2018) and SolarPower Europe (2019) outlooks. The cross-border transmission capacities in 2020 are also fixed to values from the 2018 Ten Year Network Development Plan - TYNDP (ENTSO-E, 2018).

In light of the long construction time and planning process of nuclear power, we also include exogenously the capacity additions to take place between 2020 and 2025 (accounted in 2025 in the model). These amount to 1750 MW in France (Flamanville 3), two units of 471 MW each in Slovakia (Mochovce 3 & 4) and 1750 MW in UK (Hinkley Point C) (World Nuclear Association, 2019).

*Table 13. Installed generation and storage power capacities in 2015 (in GW).*

| | Nuclear | Hard coal | Lignite | Natural gas CC | Natural gas GT | Oil | Waste | Other gases | Hydro | Biomass | Wind onshore | Wind offshore | PV | CSP | PSP | PSP* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| FI | 2.8 | 4.6 | 0.0 | 1.5 | 1.0 | 2.2 | 0.0 | 0.0 | 3.3 | 2.0 | 0.7 | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| NO | 0.0 | 0.0 | 0.0 | 1.0 | 0.7 | 0.0 | 0.0 | 0.0 | 29.9 | 0.0 | 0.7 | 0.0 | 0.0 | 0.0 | 1.4 | 11000 |
| SE | 10.0 | 0.1 | 0.0 | 0.6 | 0.3 | 4.3 | 0.0 | 0.0 | 16.2 | 4.1 | 4.6 | 0.2 | 0.0 | 0.0 | 0.1 | -- |
| EE | 0.0 | 2.0 | 0.0 | 0.4 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.4 | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| LV | 0.0 | 0.0 | 0.0 | 1.1 | 0.0 | 0.0 | 0.0 | 0.0 | 1.6 | 0.1 | 0.2 | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| LT | 0.0 | 0.0 | 0.0 | 2.6 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.1 | 0.4 | 0.0 | 0.1 | 0.0 | 0.9 | 0 |
| DK | 0.0 | 2.4 | 0.0 | 1.3 | 0.8 | 0.1 | 0.0 | 0.0 | 0.0 | 1.4 | 3.7 | 1.3 | 0.6 | 0.0 | 0.0 | 0 |
| GB | 9.4 | 17.9 | 0.0 | 28.9 | 4.1 | 1.1 | 0.0 | 0.0 | 1.7 | 1.8 | 8.5 | 4.3 | 9.1 | 0.0 | 2.7 | 33 |
| IE | 0.0 | 0.9 | 0.4 | 3.5 | 0.8 | 0.9 | 0.0 | 0.0 | 0.2 | 0.0 | 2.7 | 0.0 | 0.0 | 0.0 | 0.3 | 2 |
| NL | 0.5 | 7.5 | 0.0 | 18.2 | 2.7 | 0.0 | 0.0 | 0.0 | 0.0 | 0.4 | 2.8 | 0.4 | 1.3 | 0.0 | 0.0 | 0 |
| PL | 0.0 | 19.5 | 8.6 | 1.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.6 | 0.7 | 3.8 | 0.0 | 0.0 | 0.0 | 1.8 | 11 |
| DE | 10.8 | 28.8 | 21.2 | 22.5 | 6.7 | 2.7 | 0.8 | 2.9 | 4.0 | 7.4 | 41.0 | 3.3 | 39.8 | 0.0 | 6.4 | 39 |
| BE | 5.9 | 0.5 | 0.0 | 5.1 | 1.3 | 0.2 | 0.0 | 0.0 | 0.1 | 1.4 | 2.1 | 0.9 | 3.1 | 0.0 | 1.3 | 8 |
| LU | 0.0 | 0.0 | 0.0 | 0.4 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 1.3 | -- |
| CZ | 3.7 | 1.2 | 8.3 | 1.3 | 0.7 | 0.1 | 0.0 | 0.0 | 1.1 | 0.4 | 0.4 | 0.0 | 2.2 | 0.0 | 1.2 | 7 |

| | Nuclear | Hard coal | Lignite | Natural gas CC | Natural gas GT | Oil | Waste | Other gases | Hydro | Biomass | Wind onshore | Wind offshore | PV | CSP | PSP | PSP* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| SK | 2.3 | 0.5 | 0.6 | 1.0 | 0.2 | 0.3 | 0.0 | 0.0 | 1.6 | 0.2 | 0.0 | 0.0 | 0.5 | 0.0 | 1.0 | 4 |
| AT | 0.0 | 1.3 | 0.0 | 5.1 | 0.5 | 0.2 | 0.0 | 0.0 | 9.6 | 0.6 | 2.5 | 0.0 | 0.7 | 0.0 | 3.4 | 125 |
| CH | 3.3 | 0.0 | 0.0 | 0.1 | 0.2 | 0.0 | 0.0 | 0.0 | 11.9 | 0.3 | 0.1 | 0.0 | 1.1 | 0.0 | 1.8 | 369 |
| HU | 1.9 | 0.1 | 0.8 | 3.5 | 0.8 | 0.4 | 0.0 | 0.0 | 0.1 | 0.3 | 0.6 | 0.0 | 0.0 | 0.0 | 0.0 | 0 |
| RO | 1.3 | 1.4 | 4.4 | 2.6 | 0.1 | 0.0 | 0.0 | 0.0 | 5.2 | 0.1 | 3.0 | 0.0 | 2.0 | 0.0 | 1.3 | -- |
| SI | 0.7 | 0.3 | 1.1 | 0.1 | 0.1 | 0.0 | 0.0 | 0.0 | 1.1 | 0.0 | 0.1 | 0.0 | 0.3 | 0.0 | 0.2 | -- |
| FR | 63.1 | 3.0 | 0.0 | 6.4 | 4.5 | 8.7 | 0.0 | 0.0 | 21.0 | 0.0 | 10.3 | 0.0 | 6.2 | 0.0 | 2.5 | 184 |
| HR | 0.0 | 0.5 | 0.0 | 1.0 | 0.1 | 0.5 | 0.0 | 0.0 | 1.8 | 0.0 | 0.4 | 0.0 | 0.0 | 0.0 | 0.3 | -- |
| BG | 2.0 | 1.4 | 4.0 | 1.0 | 0.1 | 0.0 | 0.0 | 0.0 | 2.1 | 0.1 | 1.1 | 0.0 | 1.2 | 0.0 | 1.1 | 2 |
| IT | 0.0 | 9.9 | 0.0 | 45.2 | 4.2 | 8.1 | 0.0 | 0.0 | 17.0 | 4.3 | 9.6 | 0.0 | 19.3 | 0.0 | 8.2 | -- |
| ES | 7.6 | 10.0 | 1.1 | 27.5 | 5.3 | 3.5 | 0.0 | 0.0 | 13.9 | 0.9 | 23.0 | 0.0 | 4.7 | 2.3 | 6.4 | 1530 |
| PT | 0.0 | 1.8 | 0.0 | 3.4 | 1.3 | 0.1 | 0.0 | 0.0 | 4.4 | 0.6 | 4.8 | 0.0 | 0.4 | 0.0 | 1.8 | 107 |
| GR | 0.0 | 0.0 | 4.5 | 4.0 | 1.6 | 2.5 | 0.0 | 0.0 | 2.7 | 0.1 | 1.8 | 0.0 | 2.6 | 0.0 | 0.7 | 21 |
| Balkan | 0.0 | 0.0 | 7.9 | 0.0 | 0.0 | 0.2 | 0.0 | 0.0 | 5.0 | 0.0 | 0.4 | 0.0 | 0.0 | 0.0 | 3.1 | -- |

Source: Open Power System Data (2018), BMWi (2018), Platts (2011), EUROSTAT (2018b); own assumptions.

*PSP reservoir capacity (in GWh)

*Table 14. Installed generation and storage power capacities in 2020 (in GW).*

| | Nuclear | Hard coal | Lignite | Natural gas | Oil | Waste | Other gases | Hydro | Wind onshore | Wind offshore | PV | CSP | PSP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| FI | 2.8 | 2.3 | 0.0 | 1.9 | 1.4 | 1.6 | 0.1 | 3.1 | 3.1 | 0.4 | 0.1 | 0.0 | 0.0 |
| NO | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 32.6 | 2.9 | 0.0 | 0.1 | 0.0 | 0.0 |
| SE | 7.7 | 0.2 | 0.0 | 0.8 | 3.2 | 0.2 | 0.1 | 16.3 | 8.8 | 0.2 | 0.7 | 0.0 | 0.0 |
| EE | 0.0 | 0.0 | 0.0 | 0.2 | 2.0 | 0.0 | 0.0 | 0.0 | 0.5 | 0.0 | 0.0 | 0.0 | 0.0 |
| LV | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | 0.1 | 0.1 | 1.6 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 |
| LT | 0.0 | 0.0 | 0.0 | 1.8 | 0.0 | 0.0 | 0.0 | 0.1 | 0.5 | 0.0 | 0.1 | 0.0 | 0.9 |
| DK | 0.0 | 1.5 | 0.0 | 1.7 | 0.9 | 0.0 | 0.0 | 0.0 | 5.0 | 2.3 | 1.1 | 0.0 | 0.0 |
| GB | 9.2 | 10.2 | 0.0 | 31.2 | 1.2 | 0.0 | 0.0 | 1.3 | 13.6 | 9.7 | 17.1 | 0.0 | 2.9 |
| IE | 0.0 | 0.9 | 0.0 | 3.9 | 0.9 | 0.3 | 0.0 | 0.2 | 4.1 | 0.1 | 0.1 | 0.0 | 0.3 |
| NL | 0.5 | 4.0 | 0.0 | 18.5 | 0.0 | 0.4 | 0.4 | 0.0 | 5.1 | 2.4 | 10.5 | 0.0 | 0.0 |
| PL | 0.0 | 20.4 | 7.4 | 3.5 | 0.0 | 0.0 | 0.0 | 0.9 | 7.1 | 0.0 | 0.5 | 0.0 | 1.3 |
| DE | 8.1 | 18.2 | 17.6 | 23.9 | 2.1 | 2.0 | 2.0 | 5.3 | 59.5 | 7.6 | 56.2 | 0.0 | 8.0 |
| BE | 5.9 | 0.0 | 0.0 | 6.8 | 0.2 | 0.0 | 0.0 | 0.1 | 2.5 | 2.3 | 4.0 | 0.0 | 1.3 |
| LU | 0.0 | 0.0 | 0.0 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.2 | 0.0 | 0.1 | 0.0 | 1.3 |
| CZ | 4.0 | 1.6 | 8.8 | 1.3 | 0.0 | 0.0 | 0.0 | 1.0 | 0.6 | 0.0 | 2.4 | 0.0 | 1.2 |
| SK | 1.9 | 0.2 | 0.3 | 1.1 | 0.3 | 0.2 | 0.2 | 1.6 | 0.1 | 0.0 | 0.6 | 0.0 | 0.9 |
| AT | 0.0 | 0.2 | 0.0 | 4.9 | 0.2 | 0.5 | 0.5 | 5.8 | 3.9 | 0.0 | 2.0 | 0.0 | 5.9 |
| CH | 3.3 | 0.0 | 0.0 | 0.0 | 0.1 | 0.3 | 0.3 | 12.3 | 0.1 | 0.0 | 2.6 | 0.0 | 4.0 |
| HU | 1.9 | 0.0 | 1.0 | 4.1 | 0.4 | 0.0 | 0.0 | 0.1 | 0.3 | 0.0 | 0.8 | 0.0 | 0.0 |

| | Nuclear | Hard coal | Lignite | Natural gas | Oil | Waste | Other gases | Hydro | Wind onshore | Wind offshore | PV | CSP | PSP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| RO | 1.3 | 1.0 | 3.1 | 2.9 | 0.0 | 0.0 | 0.0 | 6.4 | 3.2 | 0.0 | 1.5 | 0.0 | 0.0 |
| SI | 0.7 | 0.0 | 1.0 | 0.5 | 0.1 | 0.1 | 0.1 | 1.1 | 0.0 | 0.0 | 0.3 | 0.0 | 0.2 |
| FR | 63.1 | 2.9 | 0.0 | 6.7 | 2.3 | 2.6 | 2.6 | 18.6 | 18.3 | 1.1 | 14.6 | 0.0 | 5.0 |
| HR | 0.0 | 0.3 | 0.0 | 0.7 | 1.0 | 0.0 | 0.0 | 1.8 | 0.8 | 0.0 | 0.1 | 0.0 | 0.3 |
| BG | 2.2 | 0.4 | 4.1 | 1.0 | 0.0 | 0.0 | 0.0 | 2.3 | 0.9 | 0.0 | 1.3 | 0.0 | 0.9 |
| IT | 0.0 | 7.4 | 0.0 | 45.8 | 1.3 | 0.2 | 0.2 | 15.3 | 11.3 | 0.0 | 23.9 | 0.1 | 7.6 |
| ES | 7.1 | 9.2 | 0.0 | 29.0 | 0.0 | 0.3 | 0.3 | 14.3 | 26.7 | 0.0 | 13.0 | 2.3 | 6.0 |
| PT | 0.0 | 1.8 | 0.0 | 4.6 | 0.0 | 0.0 | 0.0 | 4.3 | 5.5 | 0.0 | 1.8 | 0.0 | 2.8 |
| GR | 0.0 | 0.0 | 3.9 | 4.9 | 0.0 | 0.0 | 0.0 | 2.7 | 3.3 | 0.0 | 2.7 | 0.1 | 0.7 |
| Balkan | 0.0 | 0.0 | 8.1 | 0.5 | 0.3 | 0.0 | 0.0 | 7.5 | 1.4 | 0.0 | 0.1 | 0.0 | 1.1 |

Source: ENTSO-E (2019a), WindEurope (2018), SolarPower Europe (2019) and own assumptions.

### 5.2.2. Transmission

The cross-border transmission capacities (Table 15) correspond to the average value of NTC's in both directions for each of the existing and potential cross-border links (according to the 2018 Ten Year Network Development Plan - TYNDP (ENTSO-E, 2017a). The 2010 values are derived from the summer NTC values reported by ENTSO-E (2010). The 2015 values are derived from the ACER/CEER (2017) report. For those links for which 2015 NTC's are not reported (countries with market coupling, e.g., FR-BE), the values from 2010 are used. We also derive NTCs for 2020 (ENTSO-E, 2018), 2025 (ENTSO-E, 2019b) and 2040 (ENTSO-E, 2017a). Capacities for 2020 are also fixed due to the proximity of the year. The values for 2025 and 2040 are used as reference NTCs for different scenario analyses. 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 15. Transmission capacities between model regions (GW).*

| Link | 2010 | 2015 | 2020 | 2025 | 2040 |
|---|---|---|---|---|---|
| AT-CH | 0.8 | 1.0 | 1.2 | 1.2 | 1.7 |
| AT-CZ | 0.7 | 0.6 | 0.9 | 0.9 | 1.1 |
| AT-DE | 1.6 | 1.6 | 5.0 | 5.4 | 7.5 |
| AT-HU | 0.4 | 0.6 | 0.8 | 0.8 | 1.0 |
| AT-IT | 0.1 | 0.2 | 0.3 | 0.6 | 1.5 |
| AT-SI | 0.9 | 0.9 | 1.0 | 1.0 | 2.2 |
| AT-SK | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| BE-DE | 0.0 | 0.0 | 1.0 | 1.0 | 2.0 |
| BE-FR | 2.1 | 2.1 | 2.6 | 3.6 | 4.6 |
| BE-LU | 0.0 | 0.0 | 0.4 | 0.4 | 0.4 |
| BE-NL | 2.3 | 2.3 | 1.9 | 2.4 | 4.4 |
| BG-GR | 0.5 | 0.5 | 0.5 | 1.1 | 2.9 |
| BG-Balkan | 0.5 | 0.5 | 0.6 | 0.9 | 2.2 |
| BG-RO | 0.4 | 0.2 | 0.3 | 1.2 | 1.5 |
| CH-DE | 3.2 | 2.7 | 3.7 | 3.7 | 5.3 |
| CH-FR | 2.1 | 2.1 | 2.2 | 2.5 | 5.0 |
| CH-IT | 2.5 | 2.3 | 2.7 | 2.7 | 4.9 |
| CZ-PL | 1.4 | 0.2 | 0.7 | 0.3 | 0.7 |
| CZ-SK | 1.6 | 1.4 | 1.5 | 1.5 | 1.6 |
| DE-CZ | 1.5 | 1.7 | 1.8 | 1.8 | 2.3 |
| DE-DK | 1.8 | 1.1 | 2.6 | 4.5 | 4.0 |
| DE-FR | 2.9 | 2.9 | 2.1 | 3.0 | 5.8 |
| DE-PL | 1.0 | 0.0 | 1.8 | 1.0 | 3.3 |
| DE-SE | 0.6 | 0.6 | 0.6 | 0.6 | 2.3 |
| DK-NO | 1.0 | 1.4 | 1.6 | 1.6 | 1.6 |
| DK-SE | 1.9 | 1.9 | 2.2 | 2.2 | 3.2 |
| EE-FI | 0.4 | 0.9 | 1.0 | 1.0 | 1.0 |
| EE-LV | 0.5 | 0.7 | 0.9 | 1.0 | 1.8 |
| ES-FR | 0.9 | 1.2 | 2.7 | 5.0 | 10.0 |
| FI-SE | 1.9 | 2.4 | 2.4 | 3.2 | 4.1 |
| FR-GB | 2.0 | 1.8 | 2.0 | 4.0 | 5.9 |
| FR-IT | 1.6 | 1.7 | 3.1 | 3.2 | 3.4 |
| GB-IE | 0.2 | 0.5 | 0.5 | 1.7 | 0.5 |
| GB-NL | 0.0 | 0.0 | 1.0 | 1.0 | 1.0 |

| Link | 2010 | 2015 | 2020 | 2025 | 2040 | Link | 2010 | 2015 | 2020 | 2025 | 2040 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| GB-NO | 0.0 | 0.0 | 0.0 | 2.8 | 2.9 | NO-SE | 3.6 | 3.0 | 3.8 | 3.8 | 3.8 |
| GR-Balkan | 0.3 | 0.3 | 1.2 | 1.2 | 2.3 | PL-SE | 0.3 | 0.2 | 0.5 | 0.6 | 0.6 |
| GR-IT | 0.5 | 0.4 | 0.5 | 0.5 | 0.5 | PT-ES | 1.2 | 2.5 | 3.9 | 3.9 | 4.4 |
| HR-Balkan | 0.9 | 0.9 | 1.3 | 1.2 | 3.9 | RO-HU | 0.6 | 0.6 | 1.1 | 1.1 | 1.9 |
| HR-HU | 0.8 | 1.1 | 2.0 | 1.7 | 2.0 | RO-Balkan | 0.5 | 0.5 | 0.9 | 0.9 | 1.8 |
| HR-SI | 0.8 | 1.5 | 1.5 | 2.0 | 3.0 | SI-IT | 0.2 | 0.6 | 0.6 | 0.6 | 1.6 |
| HU-Balkan | 0.6 | 0.6 | 0.6 | 0.6 | 2.1 | SK-PL | 0.6 | 0.1 | 1.0 | 0.5 | 1.0 |
| | | | | | | DE-NO | 0.0 | 0.0 | 0.0 | 1.4 | 1.4 |
| HU-SI | 0.0 | 0.0 | 1.2 | 1.2 | 1.2 | LT-SE | 0.0 | 0.0 | 0.7 | 0.7 | 0.7 |
| HU-SK | 0.8 | 0.9 | 2.0 | 2.2 | 2.0 | IT-Balkan | 0.0 | 0.0 | 0.6 | 0.6 | 1.2 |
| LT-PL | 0.0 | 0.0 | 0.5 | 0.5 | 1.0 | BE-GB | 0.0 | 0.0 | 1.0 | 1.0 | 2.0 |
| LU-DE | 1.0 | 1.0 | 2.3 | 2.3 | 3.3 | FR-IE | 0.0 | 0.0 | 0.0 | 0.0 | 1.2 |
| LU-FR | 0.0 | 0.0 | 0.2 | 0.2 | 0.2 | GB-DK | 0.0 | 0.0 | 0.0 | 1.4 | 1.4 |
| LV-LT | 1.2 | 0.8 | 1.4 | 1.0 | 1.4 | DK-PL | 0.0 | 0.0 | 0.0 | 0.0 | 1.5 |
| NL-DE | 4.0 | 4.0 | 4.3 | 5.0 | 5.0 | DK-NL | 0.0 | 0.0 | 0.7 | 0.7 | 0.7 |
| NL-NO | 0.7 | 0.7 | 0.7 | 0.7 | 1.7 | | | | | | |

Source: ACER/CEER (2017), ENTSO-E (2010), ENTSO-E (2017a), ENTSO-E (2018), ENTSO-E (2019b); own assumptions.

## 5.3. Resource Endowments

### 5.3.1. Wind & Solar

A country's wind and solar power potential is defined by two determinants: (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 4.1.1. For capacity installed until 2020 we use the average annual availability factors between 2010 and 2015 for each technology and country (IRENA, 2017a). 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 used also 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 16 shows the technologies' capacity potentials per model region; the corresponding capacity factors per region and resource grade are given in Table 17.

*Table 16. Installable capacities of wind and solar power plants 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 |
| HU | -- | -- | 304 | -- | -- | -- | 40 | 162 | 194 | 1 | 3 | 6 |
| RO | -- | -- | 653 | -- | -- | 48 | 155 | 619 | 743 | 3 | 8 | 17 |
| SI | -- | -- | 32 | -- | -- | -- | 12 | 48 | 58 | -- | -- | 1 |

| | Wind Onshore | | | Wind Offshore | | | PV | | | CSP | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1st | 2nd | 3rd | 1st | 2nd | 3rd | 1st | 2nd | 3rd | 1st | 2nd | 3rd |
| 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[16] 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 17. 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 |
| 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 |

[16] See Section 4.1.1.

| | Wind Onshore | | | Wind Offshore | | | PV | | | CSP | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1st | 2nd | 3rd | 1st | 2nd | 3rd | 1st | 2nd | 3rd | 1st | 2nd | 3rd |
| 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.

### 5.3.2. Fuels & Hydro

As stated in Section 4.1.2, 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, biomass, 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 the calorific value of both lignite and many biofuels is too low for a cost-efficient long-distance transport. Not all regions have lignite resources; the consumption of lignite is therefore limited to those countries with existing lignite production in 2010 or 2015. In addition, we assume that new the maximum annual consumption of waste and other gases is fixed to the maximum between 2010 and 2015 levels.

The bioenergy potential is based on EEA (2006) which states the environmentally sustainable biomass potential for the EU25 Member States. We assume that two thirds of the environmentally sustainable biomass potential can be deployed at competitive prices and that the transport and heat sector demand about 50% of the available biomass stock. Therefore, only one third of the potential stated in EEA (2006) is considered eligible for electricity production in LIMES-EU. Biomass potentials of countries for which no data is available in EEA (2006) are calculated based on the extent of arable land and forests in these countries (FAO, 2018) as well as the land structure and biomass potential of the surrounding countries with available data. In case the potential calculated for a specific country is smaller than its biomass deployment target stated in the Member States' National Renewable Energy Action Plans (NREAPS) (European Commission, 2013), the potential is adjusted to cover this target[17]. Table 18 shows the maximum deployment of biomass per model region.

The limited availability of sites suitable for deploying hydropower is reflected by a maximum installable capacity of hydro power 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 current availability factors for each country. As the availability of hydro power varies significantly between years, we use an

[17] This is the case for Denmark, the Netherlands, Belgium and Luxemburg.

average of the realized capacity factors between 2006 and 2015 that are derived from IRENA (2017a). Both installable capacities and annual availability factors are shown in Table 18.

*Table 18. Regional biomass and hydropower potential.*

| | Biomass | | | Hydro | |
|---|---|---|---|---|---|
| | Annual primary energy potential (in PJ) | | | Installable capacity (GW) | Annual availability (%/a) |
| | 2010-2015 | 2020 | 2030-2050 | | |
| AT | 96 | 109 | 121 | 11.4 | 56 |
| BE | 97 | 97 | 97 | 0.2 | 33 |
| BG | 19 | 33 | 39 | 7.8 | 22 |
| CZ | 53 | 63 | 70 | 1.6 | 24 |
| DE | 432 | 472 | 603 | 5.3 | 54 |
| DK | 77 | 77 | 77 | 0 | 26 |
| EE | 21 | 31 | 36 | 0 | 49 |
| ES | 230 | 307 | 350 | 27.2 | 26 |
| FI | 134 | 137 | 131 | 3.8 | 51 |
| FR | 438 | 519 | 662 | 36.8 | 37 |
| GB | 229 | 265 | 342 | 1.7 | 36 |
| GR | 22 | 47 | 53 | 10.2 | 22 |
| HR | 34 | 36 | 39 | 3.3 | 42 |
| HU | 50 | 63 | 78 | 1.1 | 47 |
| IE | 15 | 17 | 18 | 0.4 | 36 |
| IT | 226 | 261 | 346 | 20.1 | 37 |
| LT | 57 | 106 | 138 | 0.6 | 43 |
| LU | 3 | 3 | 3 | 0 | 36 |
| LV | 18 | 27 | 33 | 2.2 | 21 |
| NL | 145 | 145 | 145 | 0.1 | 31 |
| PL | 332 | 461 | 548 | 3 | 46 |
| PT | 50 | 54 | 57 | 9.5 | 29 |
| RO | 129 | 165 | 204 | 15.4 | 30 |
| SE | 163 | 181 | 188 | 31.5 | 47 |
| SI | 25 | 24 | 25 | 2.2 | 45 |
| SK | 31 | 33 | 50 | 2.4 | 31 |

| | Biomass | | | Hydro | |
|---|---|---|---|---|---|
| | Annual primary energy potential (in PJ) | | | Installable capacity (GW) | Annual availability (%/a) |
| | 2010-2015 | 2020 | 2030-2050 | | |
| Balkan | 64 | 92 | 109 | 0 | 41 |
| CH | 34 | 40 | 49 | 13.5 | 35 |
| NO | 103 | 112 | 116 | 66.3 | 52 |

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

# 6. Emissions from 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 5). Due to the linear nature of LIMES-EU, we just assume a step-wise marginal abatement curve.

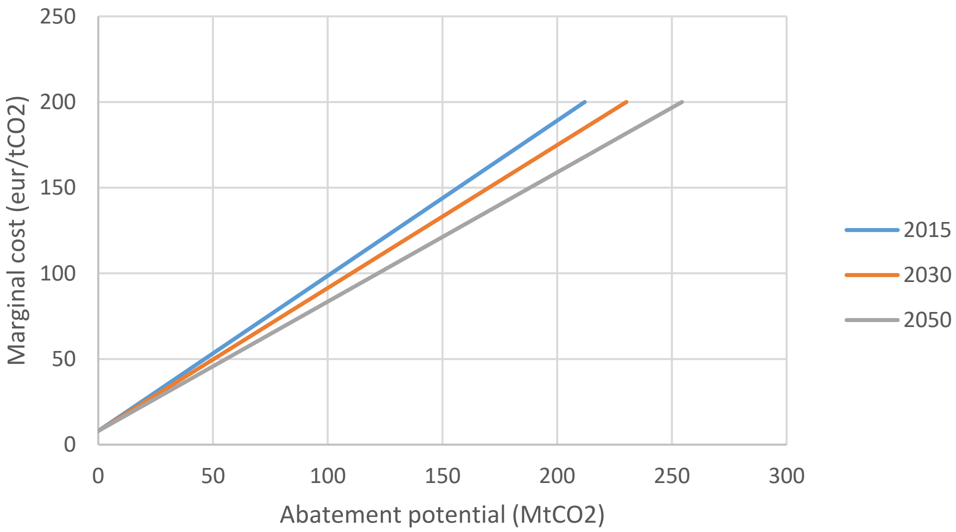
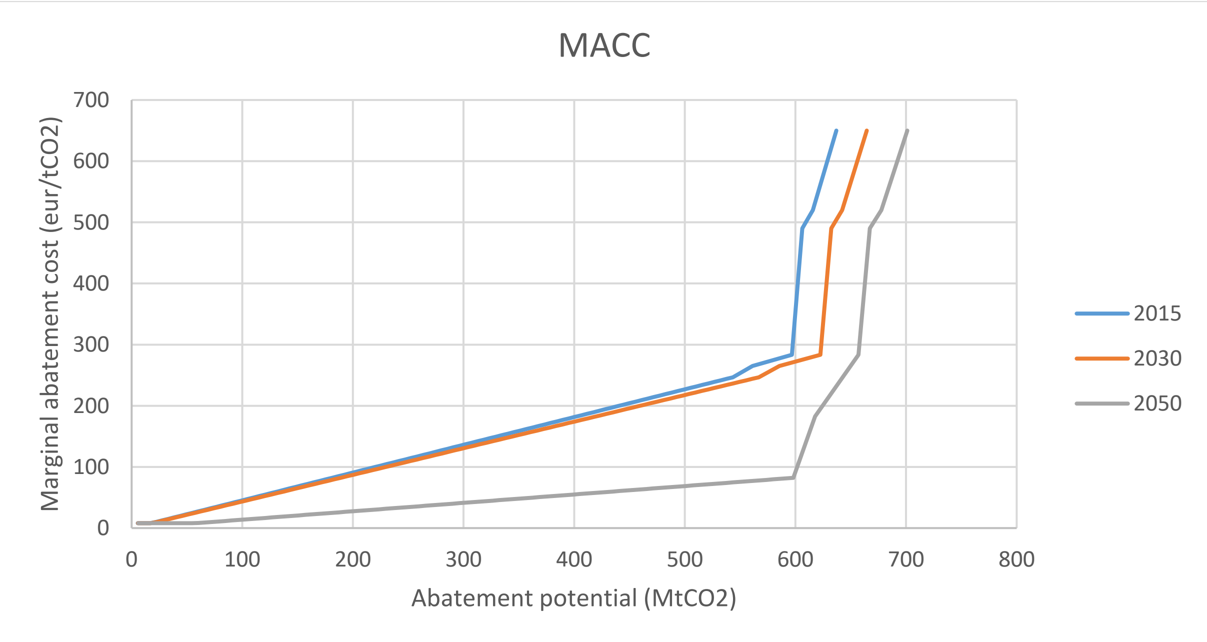



*Figure 5. Estimated MACC in 2050 for the heating-related emissions covered by the EU ETS.*

## 6.2. Energy-intensive industry

To estimate the costs of emission reductions in the energy-intensive industry, we rely on a marginal abatement cost curve (MACC). 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 constitute 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 change 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 $MtCO_2$[18]) (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 on 2050 (see Figure 6). We also assume a minimum cost of 8 €/$tCO_2$, equivalent to the assumed carbon price for 2015. Finally, we the same MACC as that for 2050 for the period afterwards.




[18] 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) reports 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.

*Figure 6. Estimated MACC in 2050 for the energy-intensive industry covered by the EU ETS.*

## 6.3. Aviation

This sector has its own cap (~37 $MtCO_2$/yr have been allocated since 2013), but is allowed to buy certificates from the stationary sector. Emissions have increased from 53 $MtCO_2$ in 2013 to 64 $MtCO_2$ in 2017, the sector having always a negative balance of EU allowances for aviation (EUAA), i.e., airlines have had to buy allowances from the stationary sector to cover their emissions. The EU forecast aviation emissions (under the current scope of the EU ETS, i.e., only covering intra-EEA flights) to be between 65 and 70 $MtCO_2$ in 2030 (EEA, 2018). In addition, it is not clear whether this scope will remain, as the current derogation from the EU ETS obligations for flights to and from third countries is extended until 31 December 2023, subject to review. There is also significant uncertainty about the future demand and technical improvements as well as on feasibility of implementing alternative fuels on a large scale (ICAO, 2016). We assume that emissions from aviation remain at 60 $MtCO_2$/yr and the cap – starting in 37 $MtCO_2$/yr in 2020 – decreases at the same pace as the stationary cap. The difference between emissions and the aviation cap are thus subtracted from the stationary cap.

## 6.4. Maritime sector

This sector will be gradually included into the EU ETS until 2026 and have its own cap, but will be allowed to buy certificates from the stationary sector. The share of allowances to be surrendered will gradually increase (with 40% for 2024 emissions, 70% for 2025 emissions and 100% of 2026 emissions) (European Commission, 2021).The EU estimates covered emissions to be around 90 $MtCO_2$ in year 2024 (European Commission, 2021). There is significant uncertainty about future emissions – the worldwide demand in 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).

We assume that emissions from the maritime sector remain at 90 $MtCO_2$/yr and the cap – starting at 36 $MtCO_2$ (40% of 90 $MtCO_2$) in 2024 – decreases at the same pace as the stationary cap. The difference between emissions and the maritime cap are thus subtracted from the stationary cap.

# 7. 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. Moreover, the EU ETS is modelled where explicit design options as certificate banking, the Market Stability Reserve (MSR) and price floors are considered as described in Appendix A.h. The emissions cap is always defined according to the research question. Most recently, LIMES has been used to estimate the impact of tighter targets -in line with the 'European Climate Law'- on the power sector.

**Renewable Policy** LIMES-EU allows for implementing technology-specific renewable energy targets for single model regions as well as implementing technology unspecific 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 as compared to 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. In order to accommodate this, their future deployment can be constrained by upper limits on investments. These limits can be set for each model region separately.

# 8. Evaluating base-year dispatch

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.

For the base year 2015, only the dispatch of generation, storage and transmission technologies is optimized by LIMES-EU. The installed capacities are given exogenously. In this Section we compare the dispatch resulting from LIMES-EU with historic electricity production data from ENTSO-E (2017b) (given the lack of fossil-based generation data for the Netherlands, we use data from Mantzos *et al.* (2018)). In addition, we compare the modelled carbon emissions with the historic emissions[19] in 2015.

In order to replicate the historic dispatch, we assume an exogenous $CO_2$ price of 8 €/t$CO_2$ which is consistent with the average price for EU ETS allowances in this year. Figure 7 gives the historic and model-based electricity generation mix of each region and of the EU28 Member States in total. The main variations occur in France, where only a small share of electricity was provided by hard coal and natural gas-fired power plants in 2015, while in the model these sources are replaced by larger nuclear generation. This is because there is only a simplified representation of CHP for Germany in the model, while in the other countries no additional revenues for heat from CHP plants are represented. Accordingly, we underestimate their dispatch.

Other regional electricity mixes deviate from historic data, e. g. hard coal is overrated in Italy and underrated in Poland. This is due to the fact that differences in prices for primary energy sources are only accounted very roughly due to lack of data. It optimizes the overall European electricity system, without considering market failures that might distort the cost-effective outcome in reality. This is certainly a drawback when aiming at reproducing historic market outcomes, but it is reasonable in order to derive benchmarks for the cost-effective future development of the European electricity system.

However, the aggregated electricity mix of the EU28 is well reproduced by the model. Only lignite is somewhat overrated while biomass and vRES generation is lower than in reality. The

[19] To estimate the electricity-related emissions, we allocate the emissions from CHP according to the share of their gross electricity output in their total output (heat and electricity) using data for the EU from Mantzos *et al.* (2018). Due to the lack of data, for Norway, Switzerland and Balkan we use emissions from public electricity and heat production from IEA (2017).

lower vRES generation is due to the higher availability factors in 2015 than those used in the model. This is explained by an improvement in technologies efficiency. Recall that we assume for capacity installed before 2015 has annual capacity factors equivalent to the average capacity factors between 2010 and 2015, e.g., the weighted average capacity factor for wind offshore in the EU between 2010 and 2015 was 30.7%, while the historical value for 2015 was 37.2% (IRENA, 2017a).

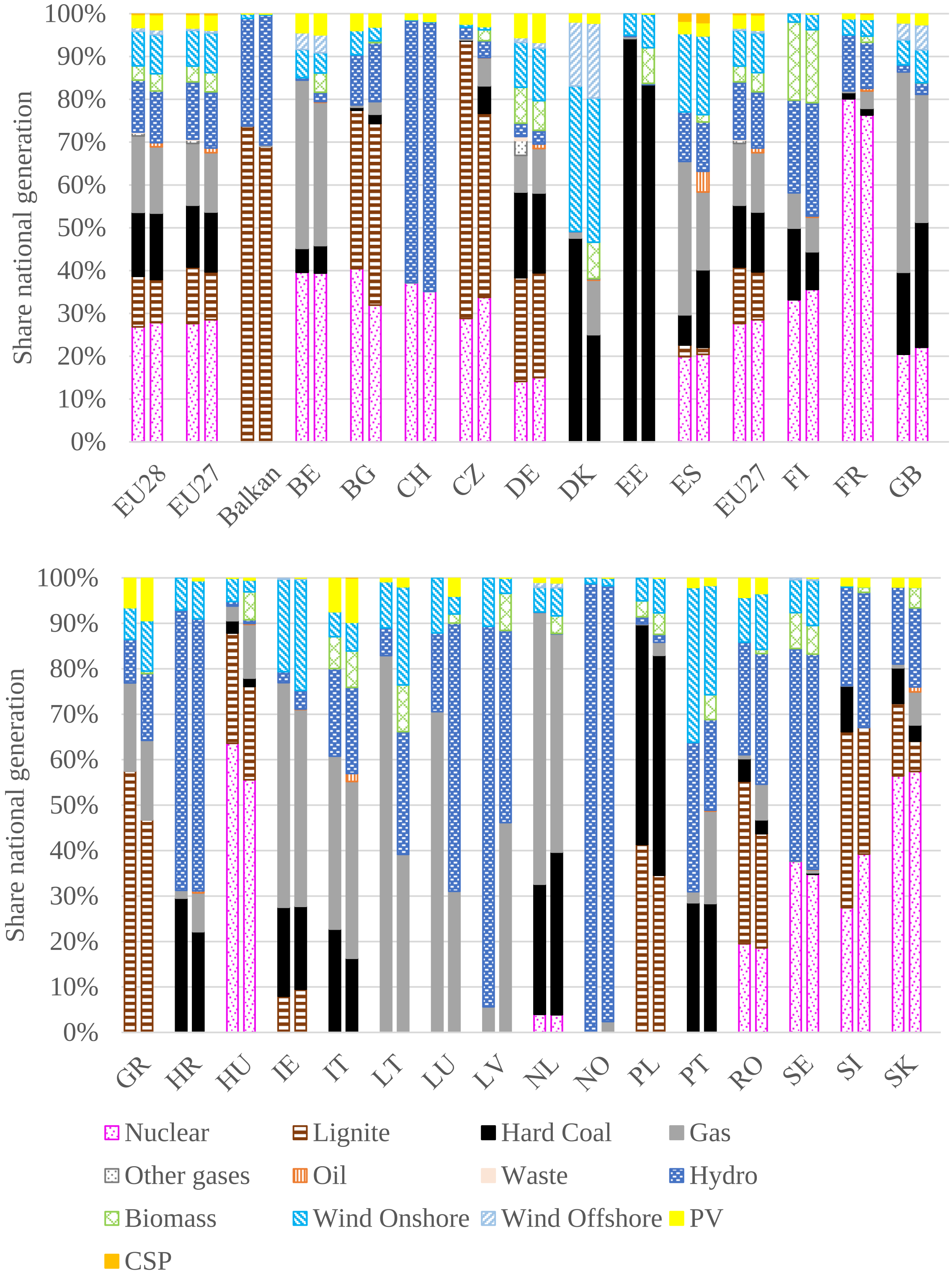



*Figure 7. Comparison of the model-derived (left bar) and the historic (right bar) region-specific electricity generation mix in 2015. Source: ENTSO-E (2017b); own model results.*

Figure 8 shows both historic emissions and model results for 2015. For Germany, we also present the historical emissions from a national source, the Öko Institute (Harthan and Hermann, 2018), which is in charge of reporting on the national emissions. This value is closer to our modelled results. As most of French generation is emission-free, this underestimation of gas and hard-coal generation leads to a sizable relative error between the modelled and historical results. However, these have little impact on EU aggregate emissions as French emissions represent a very small portion of them. Despite the simplifying model assumptions, the fit between historic emissions and model results is appropriate.

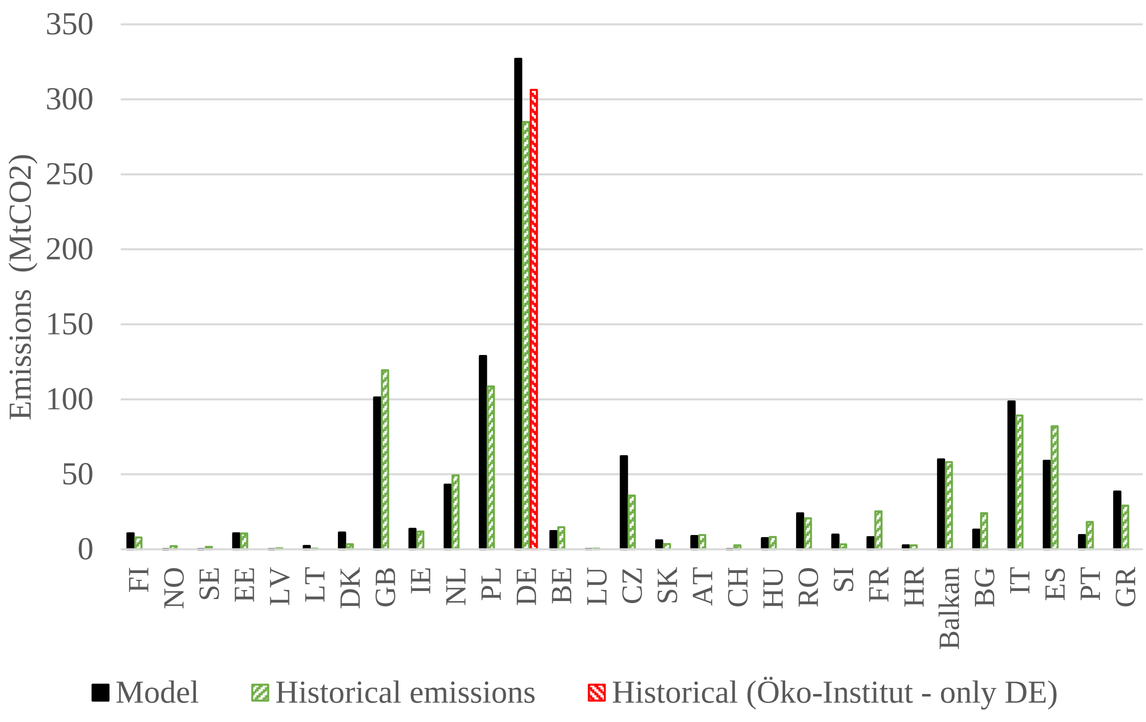



*Figure 8. Comparison of historic and modelled region-specific $CO_2$ emissions in 2015. Source: Mantzos et al. (2018), IEA (2017), Harthan and Hermann (2018); own calculations and model results.*

Although the official data for emissions in 2020 is not available yet, a rough estimation results in ~750 MtCO2[20]. Our modelled emissions are in the range of 747 and 763 $MtCO_2$, according to different setups varying the emissions constraint, transmission expansion, demand and availability of CCS. Recall there might be some variations as not all the capacities are fixed. These results suggest that calibration from 2015 also allows us to represent appropriately the electricity sector in 2020.

# 9. The impact of the number of representative days

The more representative days are included the higher the model accuracy, yet also the higher the computational effort. However, robustness of results is required to assess long-term impacts in the power sector. For instance, VREs variability has a substantial impact on market dynamics. Large amounts are desirable to reach emission targets, but might be difficult to accommodate in the grid. Hence, estimating the required investments in vRES, while still ensuring that their operation is technically feasible, is important as the short-term operation has strong implications on investments and technology choice for other technologies, i.e., on the sector long-term planning (IRENA, 2017b). It is thus of paramount importance to find a compromise between the computational efficiency[21] and the robustness of results.

We evaluate the impact of the number of representative days on a default scenario, which features the standard scenario characteristics where the EU ETS cap decreases according to current policies (i.e. a linear reduction factor of 2.2% after 2020 is assumed, see Section 7) such

[20] Electricity-related emissions in 2015, i.e., emissions from electricity-only plants plus electricity-related emissions from CHP plants, amounted to 954 $MtCO_2$ (Mantzos et al., 2018) in the EU28. This volume equals to 79% of emissions accounted within the 'combustion of fuels' category in the EU ETS (1213 $MtCO_2$) (EEA, 2019). Emission in the same category amounted to 955 $MtCO_2$ in 2019. Assuming the share of electricity-related emissions remains unchanged, we estimate electricity-related emissions to be 751 $MtCO_2$.
[21] Obtaining results for runs with less than 10 representative days take less than 24 hours, while those with 30 representative days could take up to 7 days.

that the annual cap reaches zero by 2057. We run the model with up to 30 representative days (i.e., 240 time slices per year). We show the variables related to the EU ETS (emissions and prices). We only show prices in 2030 as they rise at the interest rate (when the allowances borrowing constraint is not binding). We also show the variables that could be affected by the short-term impact of more/less renewables due to the higher model granularity, namely generation and capacity-mix at the EU ETS level.

As left panel of Figure 9 shows, emissions tend to converge for runs with more than 5 days for all the years evaluated. For instance, emissions in 2050 do not vary more than 7% (3%) in runs with more than 6 days, compared to value of 6 representative days. Likewise, carbon prices in 2030 tend to converge for runs with more than 5 days. They remain between 31 and 33 €/$tCO_2$ (see right panel of Figure 9).

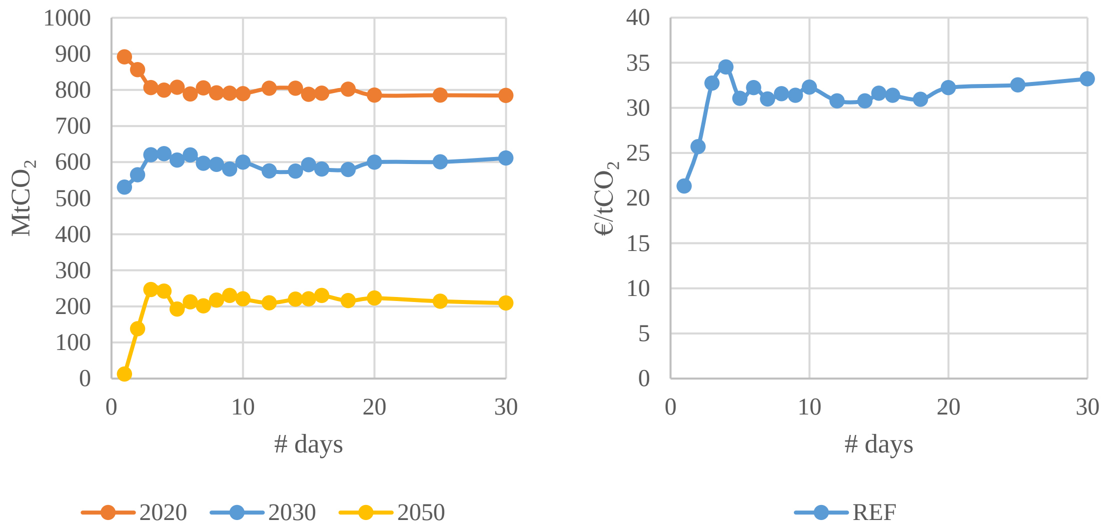
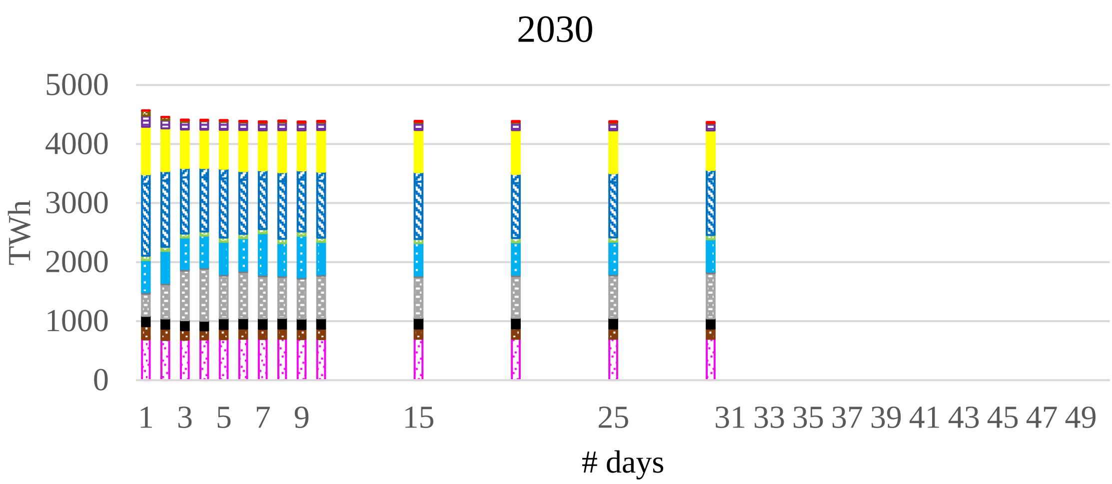



*Figure 9. Emissions in 2020, 2030 and 2050 at the EU ETS level (left panel) and carbon prices in 2030 (right panel).*

Larger differences appear in the generation-mix, although there seems to be no interaction between the number of days and the stringency of the cap. The lower granularity smooths the vRES profiles, so it is easier to accommodate their output, i.e., electricity systems are easier to decarbonise when few representative days are considered. This is highlighted by high share of RES and low share of gas generation in both 2030 and 2050 when less than 4 days are considered. In 2030, in the runs with 5-10 days, the main variations occur between gas, hydropower and wind energy. They are respectively within the range of 730 ± 50, 620 ± 80 and 1090 ± 90 TWh, i.e., a variation up to 13% of the medium value. In 2050, in the runs with 5-10 days, there appears to be an interaction between wind power and PV, whose volumes are in the range of 2330 ± 240 and 3300 ± 170, i.e., variation remains below 10%. Generation from technologies that are not deployed at large scale, but are expected to play a key role in the long-term, e.g., batteries and hydrogen-based generation, also tend to converge when more than 6 days are considered. Figure 10 also shows that variation in the generation-mix tend to decrease when 8 or more days are considered, and that figures shown by >20-days runs are similar to those obtained with 10 days.



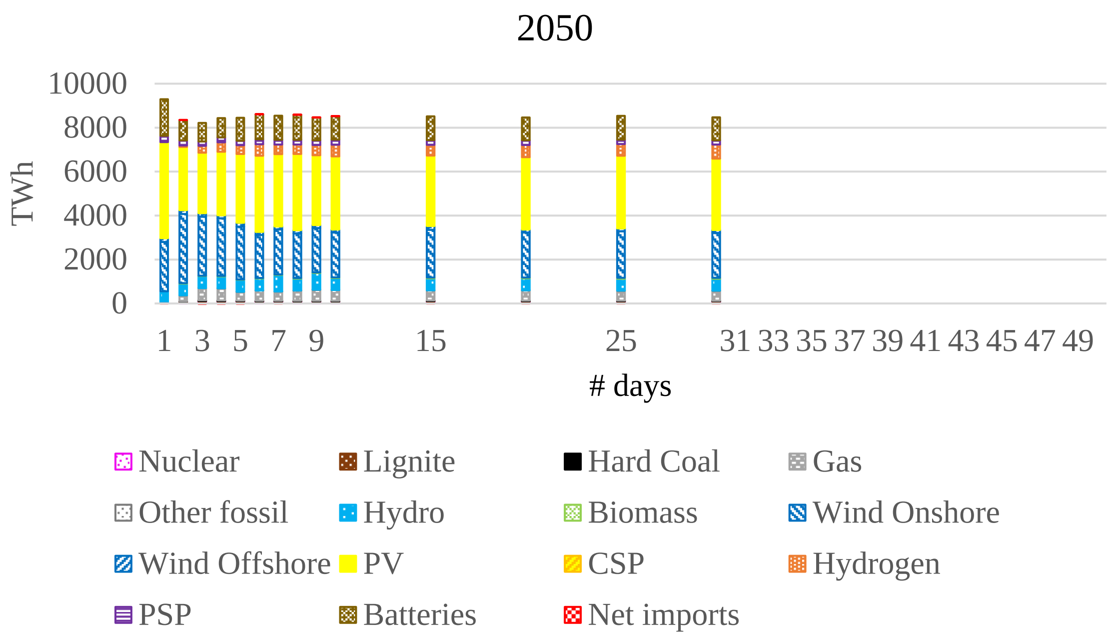



*Figure 10. Impact of modelled representative days on the generation-mix at the EU ETS level in 2030 and 2050.*

Finally, we also show the variations in the capacity-mix in 2050. Although generation is the key indicator of the level of deployment of certain technologies, estimating the magnitude of investments is of paramount importance for long-term planning. For balancing purposes, investments in some technologies might still be substantial, despite their dispatch being expected to remain low. This is particularly the case of batteries and gas-fired plants. Figure 11 shows that variation of installed capacity is similar to that of generation, and that runs with 8-10 days provide robust results of long-term investments.

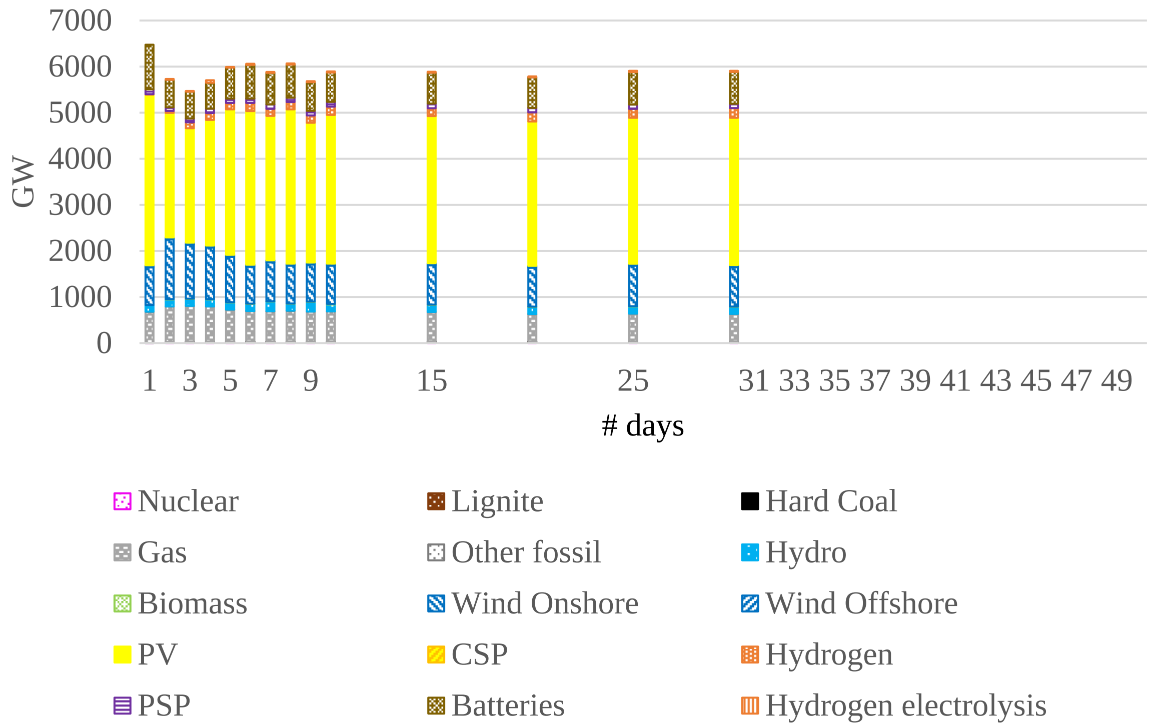



*Figure 11. Impact of modelled representative days on the capacity-mix at the EU ETS level in 2050.*

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## References

ACER/CEER, 2017. Annual Report on the Results of Monitoring the Internal Electricity and Gas Markets in 2016. Electricity Wholesale Markets Volume. Agency for the Cooperation of Energy Regulators/Council of European Energy Regulators.

Agora, 2014. Vorschlag für eine Reform der Umlage-Mechanismen im EEG. Agora Energiewende.

BFE, 2017. Statistique suisse de l'électricité 2015. Bundesamt für Energie BFE, Bern.

BFE, 2013. Perspectives énergétiques 2050. Resumé. Bundesamt für Energie BFE, Bern.

BMWi, 2018. Energiedaten: Gesamtausgabe [WWW Document]. BMWi.de. URL http://www.bmwi.de/DE/Themen/Energie/Energiedaten-und-analysen/Energiedaten/gesamtausgabe,did=476134.html (accessed 3.26.18).

Boccard, N., 2009. Capacity factor of wind power realized values vs. estimates. Energy Policy 37, 2679–2688. https://doi.org/10.1016/j.enpol.2009.02.046

Bocklet, J., Hintermayer, M., 2020. How Does the EU ETS Reform Impact Allowance Prices? The Role of Myopia, Hedging Requirements and the Hotelling Rule. EWI Work. Pap. Ser. 202001 32.

Capros, P., Dimopoulou, E., Evangelopoulou, S., Fotiou, T., Kannavou, M., Siskos, P., Zazias, G., De Vos, L., Dadkhah, A., Dekelver, G., 2018. Technology pathways in decarbonisation scenarios. ASSET.

Danish Energy Agency, Energinet, 2020. Technology Data Catalogue for Electricity and District heating production - Updated April 2020 (Catalogue). Danish Energy Agency.

de Sisternes Jimenez, F., Webster, M.D., 2013. Optimal Selection of Sample Weeks for Approximating the Net Load in Generation Planning Problems.

Dee, D.P., Uppala, S.M., Simmons, A.J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M.A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A.C.M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A.J., Haimberger, L., Healy, S.B., Hersbach, H., Hólm, E.V., Isaksen, L., Kållberg, P., Köhler, M., Matricardi, M., McNally, A.P., Monge-Sanz, B.M., Morcrette, J.-J., Park, B.-K., Peubey, C., de Rosnay, P., Tavolato, C., Thépaut, J.-N., Vitart, F., 2011. The ERA-Interim reanalysis: configuration and performance of the data assimilation system. Q. J. R. Meteorol. Soc. 137, 553–597. https://doi.org/10.1002/qj.828

DENA, 2010. dena-Netzstudie II. Integration erneuerbarer Energien in die deutsche Stromversorgung im Zeitraum 2015 – 2020 mit Ausblick 2025. Deutsche Energie-Agentur.

Domagoj Baresic, Katharine Palmer, 2021. Climate Action in Shipping. UMAS and UN Climate Change High Level Champions.

EEA, 2019. EU Emissions Trading System (ETS) data viewer [WWW Document]. Eur. Environ. Agency. URL https://www.eea.europa.eu/data-and-maps/dashboards/emissions-trading-viewer-1 (accessed 1.13.20).

EEA, 2018. Trends and projections in the EU ETS in 2018. The EU Emissions Trading System in numbers (No. 14/2018). European Environment Agency, Copenhagen.

EEA, 2006. How much bioenergy can Europe produce without harming the environment? (Publication No. 7/2006).

Enerdata, 2020. EnerFuture MACCs. Enerdata.

ENTSO-E, 2019a. Winter Outlook 2019/2020.

ENTSO-E, 2019b. Mid-term Adequacy Forecast 2019. ENTSO-E, Brussels.

ENTSO-E, 2018. Mid Term Adequacy Forecast 2018. ENTSO-E, Brussels.

ENTSO-E, 2017a. Ten-Year Network Development Plan (TYNDP) 2018.

ENTSO-E, 2017b. Production data [WWW Document]. URL https://www.entsoe.eu/data/data-portal/#consumption-data (accessed 6.5.17).

ENTSO-E, 2016. Consumption data - Hourly load values [WWW Document]. URL https://www.entsoe.eu/data/data-portal/#consumption-data (accessed 6.5.18).

ENTSO-E, 2011. Consumption data - Hourly load values [WWW Document]. URL https://www.entsoe.eu/data/data-portal/#consumption-data (accessed 6.5.18).

ENTSO-E, 2010. NTC Values Summer 2010. Final version (6 July 2010) [WWW Document]. URL https://docs.entsoe.eu/dataset/ntc-values-2006-2010 (accessed 1.24.13).

Eurelectric, VGB Powertech, 2018. Facts of Hydropower in the EU [WWW Document]. URL https://www.vgb.org/hydropower_fact_sheets_2018.html?dfid=91827

European Commission, 2021. Proposal for a Directive of the European Parliament and of the Council amending Directive 2003/87/EC establishing a system for greenhouse gas emission allowance trading within the Union, Decision (EU) 2015/1814 concerning the establishment and operation o.

European Commission, 2019. Report on the functioning of the European carbon market (Report from the Commission to the European Parliament and the Council No. COM(2019) 557 final). European Commission, Brussels.

European Commission, 2018. IN-DEPTH ANALYSIS IN SUPPORT OF THE COMMISSION COMMUNICATION COM(2018) 773 - A Clean Planet for all: A European long-term strategic vision for a prosperous, modern, competitive and climate neutral economy. Brussels.

European Commission, 2016. EU Reference Scenario 2016. Energy, transport and GHG emissions. Trends to 2050 (No. ISBN 978-92-79-52374-8). European Commission, Luxembourg.

European Commission, 2015. Proposal for a DIRECTIVE OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL amending Directive 2003/87/EC to enhance cost-effective emission reductions and low-carbon investments.

European Commission, 2013. National action plans [WWW Document]. URL /energy/en/topics/renewable-energy/national-action-plans (accessed 9.12.13).

European Parliament, Council of the European Union, 2018. Directive (EU) 2018/410 of the European Parliament and of the Council of 14 March 2018 amending Directive 2003/87/EC to enhance cost-effective emission reductions and low-carbon investments, and Decision (EU) 2015/1814. Off. J. Eur. Union 76, 3–27.

Eurostat, 2018a. Supply, transformation and consumption of electricity - annual data (nrg_105a) [WWW Document]. URL https://ec.europa.eu/eurostat/web/energy/data/database (accessed 1.16.18).

Eurostat, 2018b. Infrastructure - electricity - annual data (nrg_113a) [WWW Document]. URL http://ec.europa.eu/eurostat/en/web/products-datasets/-/NRG_113A (accessed 1.16.18).

Eurostat, 2013a. Infrastructure - electricity - annual data (nrg_113a) [WWW Document]. URL http://ec.europa.eu/eurostat/en/web/products-datasets/-/NRG_113A (accessed 1.16.13).

Eurostat, 2013b. Supply, transformation and consumption of electricity - annual data (nrg_105a) [WWW Document]. URL https://ec.europa.eu/eurostat/web/energy/data/database (accessed 7.17.13).

Fajardy, M., Dowell, N.M., 2017. Can BECCS deliver sustainable and resource efficient negative emissions? Energy Environ. Sci. 10, 1389–1426. https://doi.org/10.1039/C7EE00465F

FAO, 2018. Inputs - Land use [WWW Document]. URL http://www.fao.org/faostat/en/#data (accessed 9.12.18).

Fell, H., Burtraw, D., Morgenstern, R.D., Palmer, K.L., 2012. Soft and hard price collars in a cap-and-trade system: A comparative analysis. J. Environ. Econ. Manag. 64, 183–198. https://doi.org/10.1016/j.jeem.2011.11.004

Flachsland, C., Pahle, M., Burtraw, D., Edenhofer, O., Elkerbout, M., Fischer, C., Tietjen, O., Zetterberg, L., 2019. How to avoid history repeating itself: the case for an EU Emissions Trading System (EU ETS) price floor revisited. Clim. Policy 20, 133–142. https://doi.org/10.1080/14693062.2019.1682494

Fürsch, M., Hagspiel, S., Jägemann, C., Nagl, S., Lindenberger, D., Tröster, E., 2013. The role of grid extensions in a cost-efficient transformation of the European electricity system until 2050. Appl. Energy 104, 642–652. https://doi.org/10.1016/j.apenergy.2012.11.050

Gerbert, P., Herhold, P., Burchardt, J., Schönberger, S., Rechenmacher, F., Kirchner, A., Kemmler, A., Wünsch, M., 2018. Klimapfade für Deutschland (Study commissioned by the the Federation of German Industries (Bundesverband der Deutschen Industrie – BDI) to the Boston Consulting Group (BCG) and Prognos).

Golling, C., 2012. A cost-efficient expansion of renewable energy sources in the European electricity system - an integrated modelling approach with a particular emphasis on diurnal and seasonal patterns (PhD thesis). Universität zu Köln, Cologne.

Gomez, D., Watterson, J.D., Americano, B.B., Ha, C., Marland, G., Matsika, E., Namayanga, L., Osman-Elasha, B., Kalenga Saka, J.D., Treanton, K., Quadrelli, R., 2006. 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Volume 2. Energy. Chapter 2: Stationary combustion. IPCC.

Haller, M., Ludig, S., Bauer, N., 2012. Decarbonization scenarios for the EU and MENA power system: Considering spatial distribution and short term dynamics of renewable generation. Energy Policy 47, 282–290. https://doi.org/10.1016/j.enpol.2012.04.069

Harthan, R.O., Hermann, H., 2018. Sektorale Abgrenzung der deutschen Treibhausgasemissionen mit einem Schwerpunkt auf die verbrennungsbedingten CO2-Emissionen. Öko-Institut, Berlin.

Heck, V., Gerten, D., Lucht, W., Popp, A., 2018. Biomass-based negative emissions difficult to reconcile with planetary boundaries. Nat. Clim. Change 8, 151–155. https://doi.org/10.1038/s41558-017-0064-y

Held, A.M., 2010. Modelling the future development of renewable energy technologies in the European electricity sector using agent-based simulation (PhD Thesis). Karlsruher Insitut für Technologie, Karlsruhe.

Hirth, L., 2013. The market value of variable renewables: The effect of solar wind power variability on their relative price. Energy Econ. 38, 218–236. https://doi.org/10.1016/j.eneco.2013.02.004

Hughes, N., Strachan, N., 2010. Methodological review of UK and international low carbon scenarios. Energy Policy, The socio-economic transition towards a hydrogen economy -

findings from European research, with regular papers 38, 6056–6065. https://doi.org/10.1016/j.enpol.2010.05.061

ICAO, 2016. On board. A sustainable future. 2016 Environmental report. International Civil Aviation Authority (ICAO).

IEA, 2019. Offshore Wind Outlook 2019. OECD/IEA, Paris France.

IEA, 2017. CO2 emissions from fuel combustion. Highlights. International Energy Agency, Paris.

IEA PVPS, 2021. Trends in PV applications 2020.

IRENA, 2018. Query Tool [WWW Document]. Stat.-Data--Top.--Gener.-Tool. URL /Statistics/View-Data-by-Topic/Capacity-and-Generation/Query-Tool (accessed 12.16.19).

IRENA, 2017a. Renewable Electricity Capacity and Generation Statistics [WWW Document]. URL http://resourceirena.irena.org/gateway/dashboard/index.html?topic=4&subTopic=54 (accessed 3.20.18).

IRENA, 2017b. Planning for the renewable future: Long-term modelling and tools to expand variable renewable power in emerging economies. Abu Dhabi, UAE.

IZES, BET, PowerEngs, 2011. Ausbau elektrischer Netze mit Kabel oder Freileitung unter besonderer Berücksichtigung der Einspeisung Erneuerbarer Energien (Report by IZES gGmbH, BET GmbH and PowerEngS on behalf of the BMU).

Mantzos, L., Matei, N.A., Mulholland, E., Rozsai, M., Tamba, M., Wiesenthal, T., 2018. JRC-IDEES 2015 [Dataset]. European Commission, Joint Research Centre (JRC).

Markewitz, P., Robinius, M., Stolten, D., Markewitz, P., Robinius, M., Stolten, D., 2018. The Future of Fossil Fired Power Plants in Germany—A Lifetime Analysis. Energies 11, 1616. https://doi.org/10.3390/en11061616

Nagl, S., Fürsch, M., Lindenberger, D., 2013. The Costs of Electricity Systems with a High Share of Fluctuating Renewables: A Stochastic Investment and Dispatch Optimization Model for Europe. Energy J. 34, 151–179.

Nahmmacher, P., Schmid, E., Hirth, L., Knopf, B., 2016. Carpe diem: A novel approach to select representative days for long-term power system modeling. Energy 112, 430–442. https://doi.org/10.1016/j.energy.2016.06.081

Nahmmacher, P., Schmid, E., Knopf, B., 2014. Documentation of LIMES-EU - A long-term electricity system model for Europe [WWW Document]. URL https://www.pik-potsdam.de/research/transformation-pathways/models/limes/DocumentationLIMESEU_2014.pdf/view

NEP, 2013. Netzentwicklungsplan Strom 2013 - zweiter Entwurf der Übertragungsnetzbetreiber, Anhang.

NGDC, N.G.D.C., 2013. ETOPO1 Global Relief [WWW Document]. URL https://www.ngdc.noaa.gov/mgg/global/ (accessed 9.13.13).

NREL, 2013. Global CFDDA-based Onshore and Offshore Wind Potential Supply Curves by Country, Class, and Depth (quantities in GW and PWh) - OpenEI DOE Open Data [WWW Document]. URL https://openei.org/doe-opendata/dataset/global-cfdda-based-onshore-and-offshore-wind-potential-supply-curves-by-country-class-and-depth-q (accessed 6.5.18).

Ong, S., Campbell, C., Denholm, P., Margolis, R., Heath, G., 2013. Land-Use Requirements for Solar Power Plants in the United States (Technical Report No. NREL/TP-6A20-56290). National Renewable Energy Laboratory (NREL).

Open Power System Data, 2018. National generation capacity [WWW Document]. URL https://data.open-power-system-data.org/national_generation_capacity/2017-07-07/ (accessed 6.5.18).

Ottmar Edenhofer, Flachsland, C., Wolff, C., Schmid, L.K., Leipprand, A., Koch, N., Kornek, U., Pahle, M., 2019. Decarbonization and EU ETS Reform: Introducing a price floor to drive low-carbon investments, in: 12 Years of European Emissions Trading in Germany. Stocktaking and Perspectives for Effective Climate Protection. Metropolis, pp. 207–232.

Pietzcker, R.C., Osorio, S., Rodrigues, R., 2021. Tightening EU ETS targets in line with the European Green Deal: Impacts on the decarbonization of the EU power sector. Appl. Energy 293, 116914. https://doi.org/10.1016/j.apenergy.2021.116914

Pietzcker, R.C., Stetter, D., Manger, S., Luderer, G., 2014. Using the sun to decarbonize the power sector: The economic potential of photovoltaics and concentrating solar power. Appl. Energy 135, 704–720. https://doi.org/10.1016/j.apenergy.2014.08.011

Platts, 2011. UDI World Electric Power Plants Data Base (September 2011). S&P Global Platts.

Poncelet, K., Höschle, H., Delarue, E., Virag, A., D'haeseleer, W., 2017. Selecting Representative Days for Capturing the Implications of Integrating Intermittent Renewables in Generation Expansion Planning Problems. IEEE Trans. Power Syst. 32, 1936–1948. https://doi.org/10.1109/TPWRS.2016.2596803

Quemin, S., 2020. Using supply-side policies to raise ambition: the case of the EU ETS and the 2021 review. Grantham Research Institute on Climate Change and the Environment.

Quemin, S., Trotignon, R., 2019. Emissions trading with rolling horizons. J. Econ. Dyn. Control 125, 104099. https://doi.org/10.1016/j.jedc.2021.104099

Rehfeldt, M., Fleiter, T., Herbst, A., Eidelloth, S., 2020. Fuel switching as an option for medium-term emission reduction - A model-based analysis of reactions to price signals and regulatory action in German industry. Energy Policy 147, 111889. https://doi.org/10.1016/j.enpol.2020.111889

Reuß, M., Grube, T., Robinius, M., Preuster, P., Wasserscheid, P., Stolten, D., 2017. Seasonal storage and alternative carriers: A flexible hydrogen supply chain model. Appl. Energy 200, 290–302. https://doi.org/10.1016/j.apenergy.2017.05.050

Saba, S.M., Müller, M., Robinius, M., Stolten, D., 2018. The investment costs of electrolysis – A comparison of cost studies from the past 30 years. Int. J. Hydrog. Energy 43, 1209–1223. https://doi.org/10.1016/j.ijhydene.2017.11.115

Schaber, K., Steinke, F., Hamacher, T., 2012. Transmission grid extensions for the integration of variable renewable energies in Europe: Who benefits where? Energy Policy 43, 123–135. https://doi.org/10.1016/j.enpol.2011.12.040

Schmidt, O., Melchior, S., Hawkes, A., Staffell, I., 2019. Projecting the Future Levelized Cost of Electricity Storage Technologies. Joule 3, 81–100. https://doi.org/10.1016/j.joule.2018.12.008

Short, W., Sullivan, P., Mai, T., Mowers, M., Uriarte, C., Blair, N., Heimiller, D., Martinez, A., 2011. Regional Energy Deployment System (ReEDS) (Technical Report No. NREL/TP-6A20-46534). National Renewable Energy Laboratory (NREL), Colorado.

SolarPower Europe, 2019. Global Market Outlook For Solar Power 2019 - 2023 (Solar Industry Reports).

Steward, D., Saur, G., Penev, M., Ramsden, T., 2009. Lifecycle Cost Analysis of Hydrogen Versus Other Technologies for Electrical Energy Storage (Technical Report No. NREL/TP-560-46719). National Renewable Energy Laboratory (NREL).

Strefler, J., Kriegler, E., Bauer, N., Luderer, G., Pietzcker, R., Giannousakis, A., Edenhofer, O., 2021. Alternative carbon price trajectories can avoid excessive carbon removal. Nat. Commun. Accepted.

Trieb, F., Schillings, C., O Sullivan, M., Pregger, T., Hoyer-Klick, C., 2009. Global Potential of Concentrating Solar Power. Presented at the SolarPaces Conference, Berlin.

UBA, 2018. Wirkungsgrade und spezifische Kohlendioxid-Emissionen verschiedener Kraftwerkstypen [WWW Document]. Umweltbundesamt. URL https://www.umweltbundesamt.de/sites/default/files/medien/384/bilder/dateien/7_abb_wirkungsgrade-spez-co2-emissionen_2018-02-14.pdf (accessed 10.26.18).

ÜNB, 2013a. Wind & Photovoltaic Infeed 2011 [WWW Document]. URL http://www.50hertz.comhttp://www.tennettso.dehttp://www.amprion.nethttp://www.transnetbw.de (accessed 6.13.13).

ÜNB, 2013b. EEG-Anlagenstammdaten 2011 [WWW Document]. URL http://www.eeg-kwk.net/de/ Anlagenstammdaten.htm (accessed 8.3.13).

Ward, J.H., 1963. Hierarchical Grouping to Optimize an Objective Function. J. Am. Stat. Assoc. 58, 236–244. https://doi.org/10.1080/01621459.1963.10500845

Willner, M., 2018. Consulting the Chrystal Ball: Firms’ Foresight and a Cap-and-Trade Scheme with Endogenous Supply Adjustments. SSRN Electron. J. https://doi.org/10.2139/ssrn.3231927

WindEurope, 2018. Wind energy in Europe: Outlook to 2022. WindEurope Business Intelligence.

World Nuclear Association, 2019. Information Library - World Nuclear Association [WWW Document]. URL https://www.world-nuclear.org/Information-Library.aspx (accessed 1.8.20).

# 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 |
| $\tau$ | time slices |
| *r* | regions |
| *rg* | vRES resource grades |
| *te* | electricity generation technologies |
| *st* | storage technologies |
| *cn* | transmission connections |
| *pe* | primary energy types |
| *s* | sector (e.g., electricity) |
| $m$ | abatement measure |
| *sn* | season |

*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* |
| $TE$ | all electricity generation technologies |

| Symbol | Description |
|---|---|
| $TE_{pe}$ | 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 |

*Table A3. Parameters.*

| Symbol | Description |
|---|---|
| $\rho$ | discount rate |
| $\Delta t$ | time span (in years) between model years |
| $l_\tau$ | length of time slice $\tau$ |
| $\lambda_{pe}$ | emission factor of primary energy *pe* |
| $\psi_{te}, \psi_{st}, \psi_{cn}$ | lifetime of technology *te* / storage *st* / connection *cn* |
| $\mu_{te}$ | minimum load of technology *te* |

| Symbol | Description |
| --- | --- |
| $\delta$ | minimum annual load |
| $\varphi_r$ | 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 |
| $\eta_{te}, \eta_{st}$ | conversion efficiency |
| $\gamma_{cn}$ | 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 |
| $euaa^{CO_2}_t$ | EU allowances used by the aviation sector |
| $e^{CO_2}_{t,avi}$ | $CO_2$ emissions from the aviation sector |
| $cap\_mar^{CO_2}_t$ | $CO_2$ emissions cap for the maritime sector |
| $euam^{CO_2}_t$ | EU allowances used by the maritime sector |
| $e^{CO_2}_{t,mar}$ | $CO_2$ emissions from the maritime sector |
| $a_{te}$ | auto-consumption rate |

| Symbol | Description |
|---|---|
| $r_{te}$ | ramping factor |
| $f_{te}$, $f_{st}$ | firm capacity factor for *te*, *st* and imports |
| $rm$ | reserve margin |
| $\vartheta^{RK}$ | maximum share of reserves in demand |
| μ | minimum share of hydrogen produced by electrolysis within the model regions |
| $\theta$ | number of cycles in hydrogen storage |
| $h_{t,r}^{OS}$ | hydrogen demand from other sectors |

*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 |
| $K_{t,r,te}$, $K_{t,r,st}$, $K_{t,cn}$ | 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 |
| $K_{(t-\tilde{t}),r,te,rg}^{RG}$ | installed capacity (resource grade specific) |
| $\Delta K_{(t-\tilde{t}),r,te,rg}^{RG}$ | new capacity (resource grade specific) |
| $G_{t,\tau,r,te}$ | electricity generation |
| $E_{t,r,s}^{CO_2}$ , $E_{t,s}^{CO_2}$ | $CO_2$ emissions |
| $E_{t,r,elec}^{CCS}$ | captured $CO_2$ (via CCS) |
| $S_{t,\tau,r,st}^{IN}$, $S_{t,\tau,r,st}^{OUT}$ | storage input/output |
| $L_{t,\tau,r,st}$ | storage level |

| Symbol | Description |
|---|---|
| $F^{+}_{t,\tau,cn}$, $F^{-}_{t,\tau,cn}$ | 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 |

### a. Objective function

Equation (A.1): Objective function

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

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

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

### 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

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

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

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

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

Equation (A.33): Reservoir level

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

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 ($\theta$)

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

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

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

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

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

### 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

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

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

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

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

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

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

$$\sum_{\tau} l_\tau H^{OS}_{t,\tau,r} + IH^{OS}_{t,r} = h^{OS}_{t,r} \qquad \forall\, t,r \tag{A.42}$$

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

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

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

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

Equation (A.45): Captured $CO_2$ emissions

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

Equation (A.46): CCS storage constraint

$$\Delta t \sum_{t} E^{CCS}_{t,r,elec} \leq cap_r^{CCS_{cum}} \qquad \forall\, r \tag{A.46}$$

## g. Security of supply

Equation (A.47): Robustness condition

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

Equation (A.48): Reserves constraint

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

$$RK_{t,r,te} \leq RK_{t-1,r,te} + \Delta t \sum_{tt} DK_{t,tt,r,te} \qquad \forall\, t,r,te$$

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[22]. 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.

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

[22] 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., $t = 2015,2020 \dots .2055$), while *t2* is only used for those related to the MSR simulation (annual basis, i.e., $t2 = 2017,2018 \dots .2057$).

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

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

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

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

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

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

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

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

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

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

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

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

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[23]. 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[24] 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.

[23] 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

[24] 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

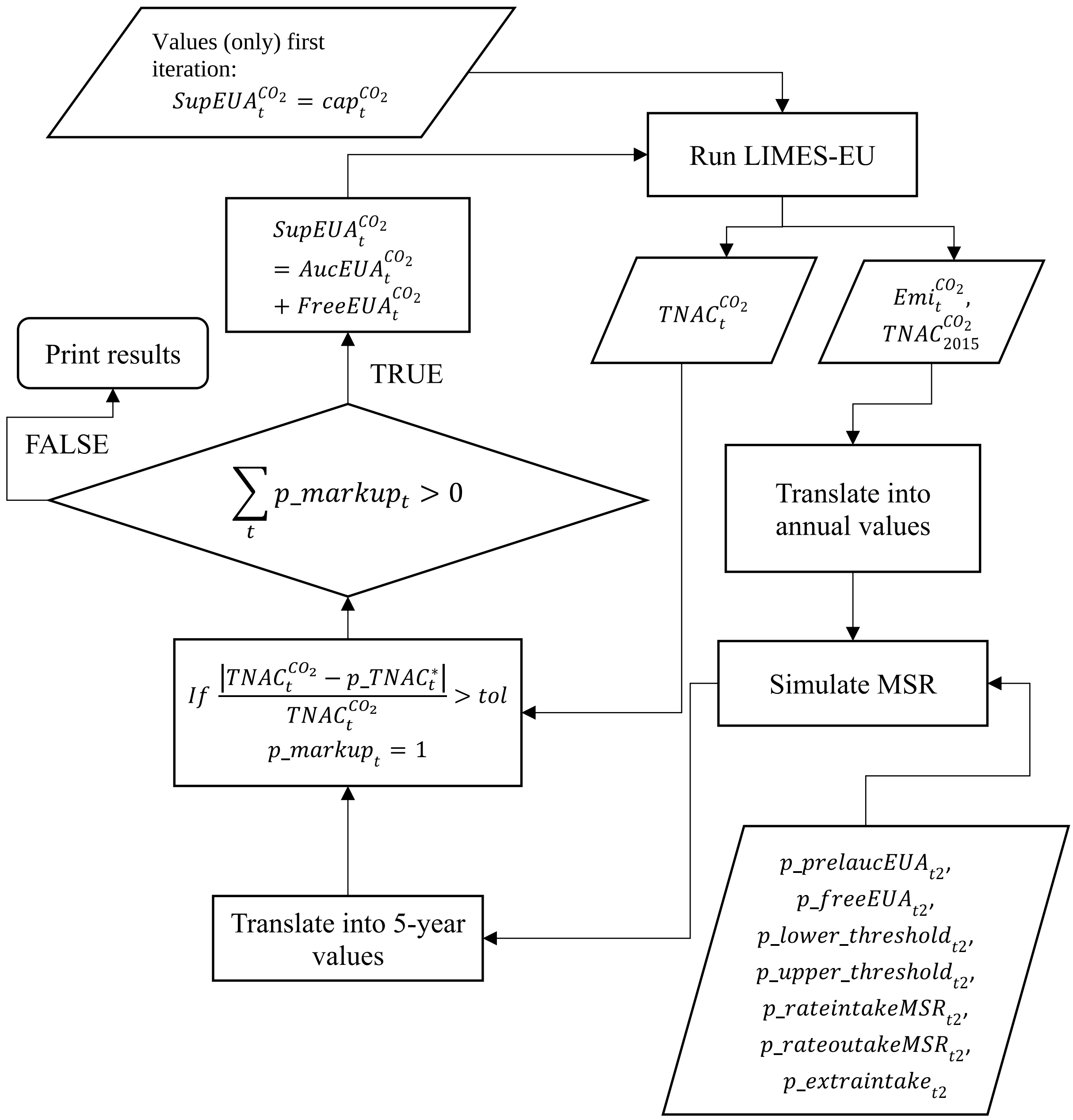


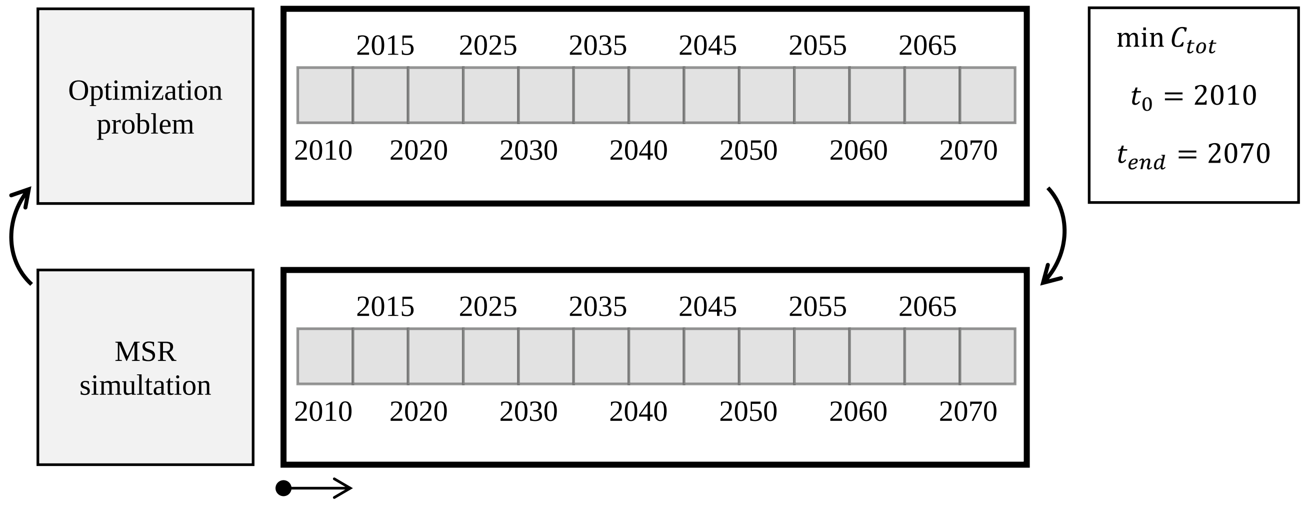

*Figure A1. Iterative process to couple LIMES-EU with the MSR simulation.*

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).

**Perfect Foresight**




**Myopic Foresight**

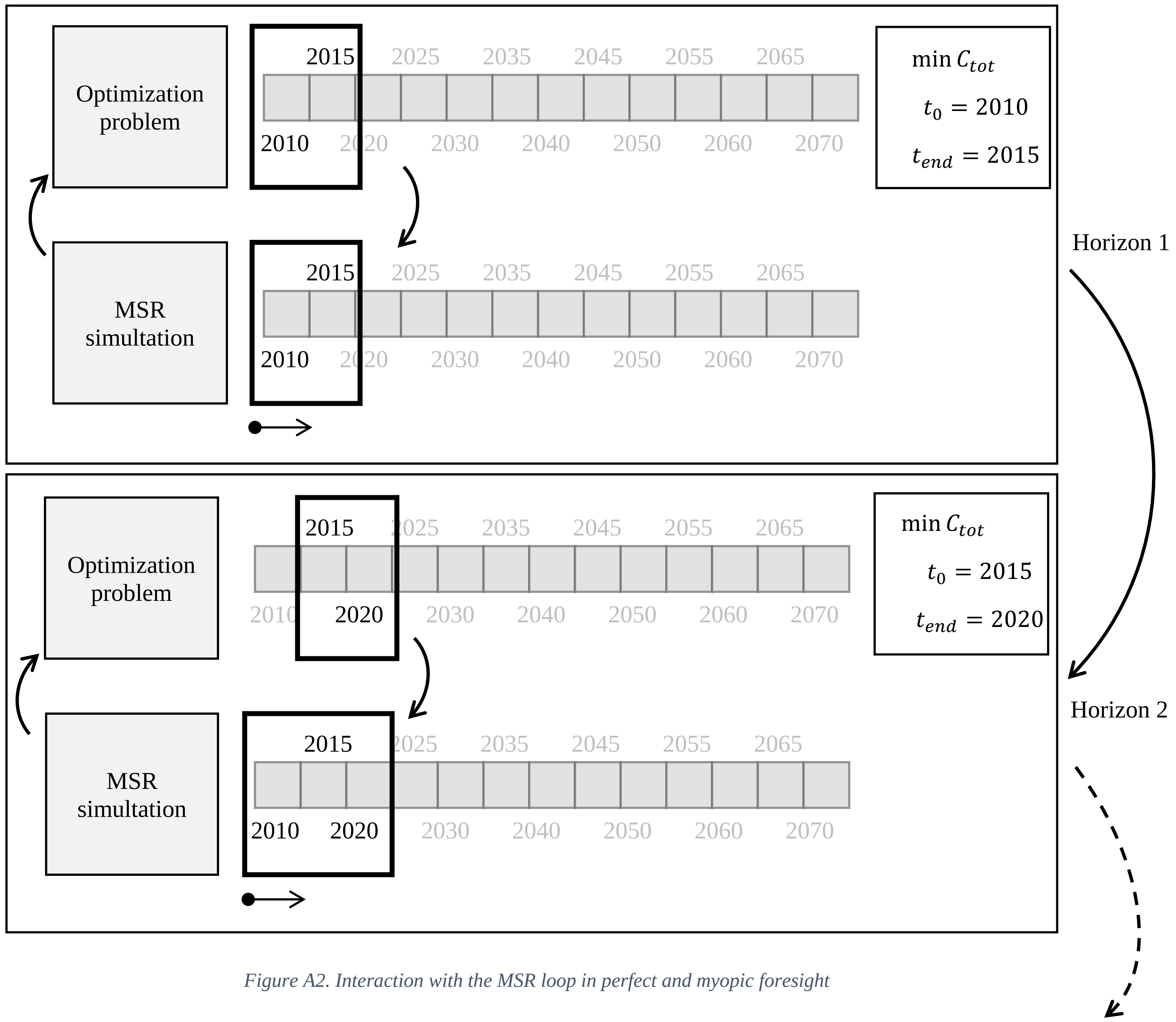



*Figure A2. Interaction with the MSR loop in perfect and myopic foresight*

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 modeling 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.

### *h.3. Carbon price floor (CPF)*

A carbon price floor is a policy gaining momentum as an alternative to decarbonize the electricity sector, in particular given the success of its implementation in UK. The interaction between this and the EU ETS remains nonetheless complex and requires a proper analysis. Its implementation in LIMES-EU is not straightforward as a carbon price floor implies non-linear conditions. We consider two different types of price floors. First, EU ETS countries may issue less allowances in order to raise the ETS price. Second, EU ETS countries may put a top-up on the ETS price without issuing fewer allowances which corresponds to the UK price floor.

The first case is straightforward to implement in the model. In doing so, we follow Fell et al. (2012). Fell *et al.* (2012) formulate a model that allows estimating the amount of certificates required to be withdrawn from a cap-and-trade system (e.g. the EU ETS) in order to reach a CPF. We accordingly modify the objective function (Eq. (A.1)) to include the costs of withdrawing EUA (see Eq. (A.65)), where the parameter $cpf_t$ is the previously defined carbon price floor for the entire EU ETS, and the variable $Efloor_t$ is the volume of EUA withdrawn. The latter ($Efloor_t$) also affects the TNAC, and thus Eq. (A.66) replaces Eq. (A.55).

$$C^{tot} = \sum_t \left( \Delta t \, e^{-\rho(t-t_0)} \left( C_t^I + C_t^F + C_t^{OM} + C_t^{CO_2} - \boldsymbol{cpf_t} \times \boldsymbol{Efloor_t} \right) \right) - e^{-\rho(t_{end}-t_0)} V \qquad \text{(A.65)}$$

$$TNAC_t^{CO_2} = TNAC_{t-1}^{CO_2} + \Delta t \left( Seua_t^{CO_2} - Emi_t^{CO_2} - \boldsymbol{Efloor_t} \right) \qquad \forall\, t \leq T_{ETS} \qquad \text{(A.66)}$$

The second case, where some EU members implement unilaterally their own CPF, is more complicated because the $CO_2$ price in LIMES-EU results from the shadow price of the emissions constraint (banking, cap or budget). The formulation from Fell *et al.* (2012)does not work when only one country or a group of countries within a cap-and-trade system implement a top-up tax in order to reach a CPF, because the total emission constraint results in only one $CO_2$ price for all the countries belonging to the cap-and-trade system. We thus develop an iterative process that allows us implement any top-up $CO_2$ tax in any country within a larger ETS (see Figure A3).

In a first iteration (*i=1*) the model is run with only the emissions constraint and no exogenous top-up $CO_2$ tax ($x_{t,r,i} = 0$). The carbon price in the model ($P_{t,i}$) results from the EUA banking constraint (Eq. (A.55)). If $P_{t,i}$ is lower than the desired CPF ($P_{t,r}^*$) (considering a tolerance parameter $tol = 0.01$), the model is run again. In a second iteration we run the model assuming an exogenous $CO_2$ price, i.e., the needed top-up $CO_2$ tax, which equals the difference between

$P^*_{t,r}$ and $P_{t,i}$ (see Figure A4). We thus iterate until the resulting $CO_2$ price from two consecutive iterations converge.

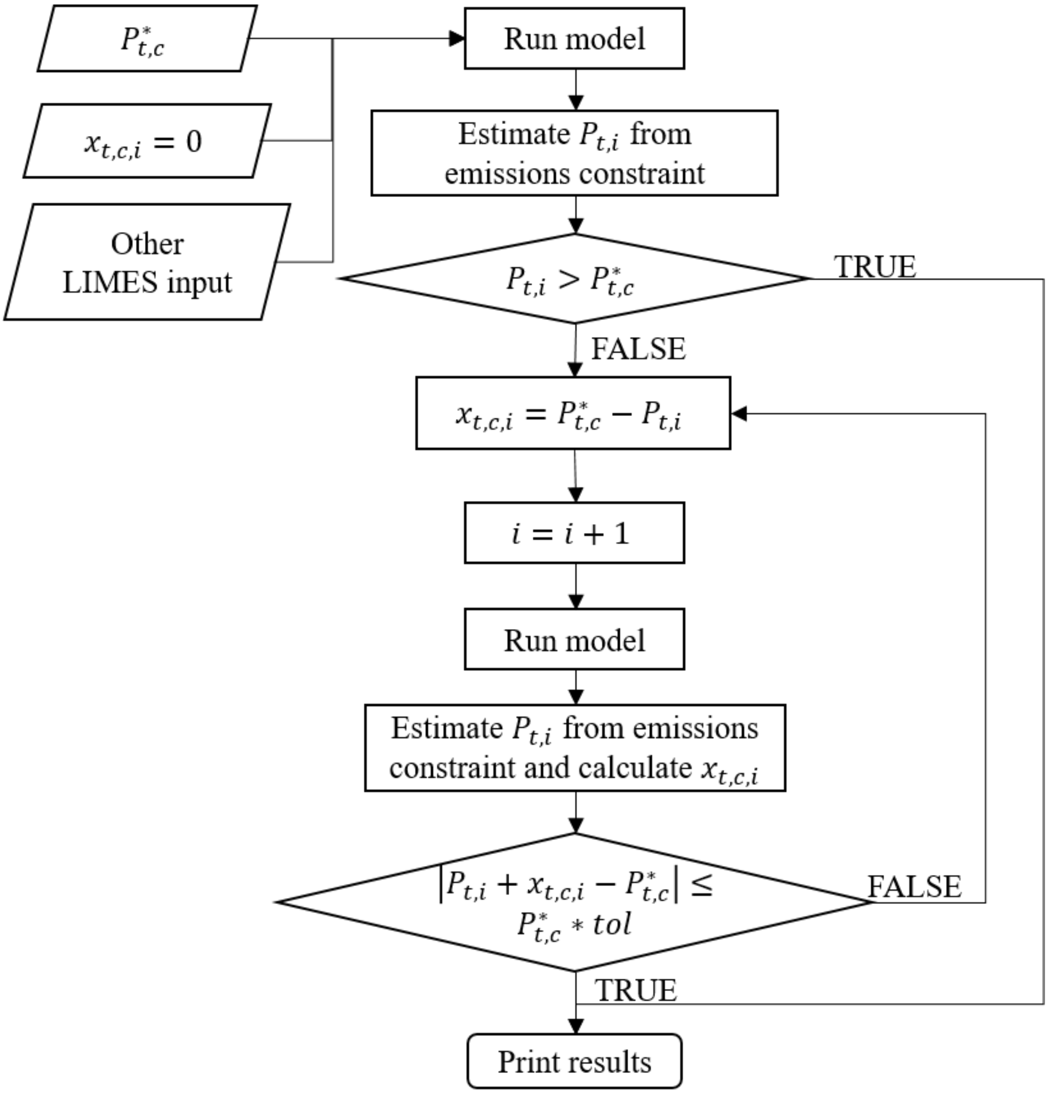



*Figure A3. Flow diagram explaining the iterative process formulated to run the model when a minimum $CO_2$ price is implemented.*

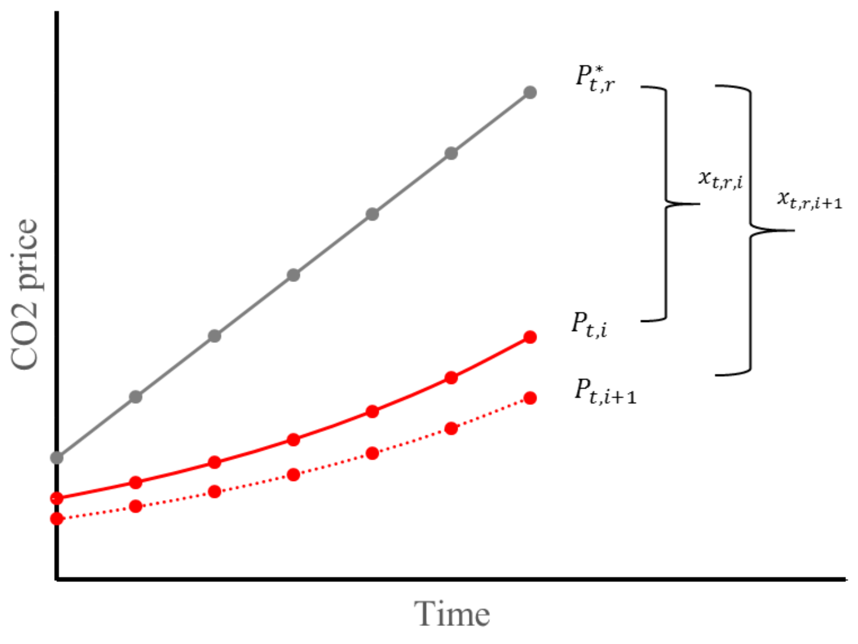



*Figure A4. Top-up $CO_2$ price adjustment between two iterations for countries implementing a minimum $CO_2$ price.*

### i. Other electricity sector policies

Equation (A.67): $CO_2$ emission target for a group of regions

$$\sum_{r \in R^{pol}} E^{CO_2}_{t,r,elec} \leq cap^{CO_2}_t \qquad \forall\, t \tag{A.67}$$

Equation (A.68): $CO_2$ emission target for a single region

$$E^{CO_2}_{t,r,elec} \leq cap^{CO_2}_{t,r} \qquad \forall\, t, r \tag{A.68}$$

Equation (A.69): $CO_2$ budget for a group of regions

$$\Delta t \sum_{t} \sum_{r \in R^{pol}} E^{CO_2}_{t,r,elec} \leq bud^{CO_2} \tag{A.69}$$

Equation (A.70): $CO_2$ budget for a single region

$$\Delta t \sum_{t} E_{t,r,elec}^{CO_2} \leq bud_r^{CO_2} \qquad \forall\, r \tag{A.70}$$

Equation (A.71): National RES target

$$\sum_{\tau} l_\tau \sum_{te\, \in TE^{RES}} G_{t,\tau,r,te} \geq res_{t,r} \qquad \forall\, t, r \tag{A.71}$$

Equation (A.72): Target on minimum amount of electricity provided domestically

$$\sum_{\tau} l_\tau \sum_{te\, \in TE^{RES}} G_{t,\tau,r,te} \geq \phi_r \sum_{\tau} l_\tau d_{t,\tau,r} \qquad \forall\, t, r \tag{A.72}$$

# 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 |

| Region code | Region name |
|---|---|
| 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 |