A multi-horizon stochastic programming model for the European power system

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Abstract

This paper presents the stochastic power system investment model EMPIRE. Formulated as a multi-horizon stochastic program EMPIRE incorporates long-term and short-term system dynamics, while optimizing investments under operational uncertainty. By decoupling the optimization of system operation at each investment period from future investment and operation periods, a computationally tractable optimization problem is produced. The use of EMPIRE is illustrated in a decarbonization study of the European power system for two cases, one with transmission infrastructure investments, and one without. A combination of onshore wind and thermal generation with carbon capture and storage (CCS) is shown to provide significant CO_2 emission reductions from 2010 to 2050, 85 % in the transmission expansion case and 82 % in the no expansion case.

1 Introduction

As a response to the challenge to mitigate climate change the European Commission (EC) has supported a long-term commitment to reduce domestic greenhouse gas emissions in the European Union by 80–95 %, relative to 1990 levels (EC, 2009). In its 2011 "Energy Roadmap 2050" the EC shows that reaching this target will entail an almost complete decarbonization of the power sector (EC, 2011). This necessitates a large-scale deployment of renewable electricity production, in particular wind and solar power. However, owing to the intermittent and non-controllable nature of wind and solar generation, an increased share of these technologies in the generation mix imposes challenges in terms of balancing supply and demand. These aspects introduce short-term uncertainty which is important to consider when planning investments of generation technologies, transmission system and energy storage equipment throughout the system.

In this paper we present a stochastic programming model, EMPIRE (European Model for Power system Investment with Renewable Energy), developed to handle the challenges related to intermittent energy production and stochastic energy demand in a long-term investment model. To avoid the curse of dimensionality when modeling short-term uncertainty in a long-term model, we use the multi-horizon approach presented by Kaut et al. (2014). The main contribution of this model is that it simultaneously handles short-term dynamics, short-term uncertainty as well as long-term dynamics. We are not aware of other long-term spatial power sector models that do so, and we think these properties are critical when modeling the need for storage and other technologies, as a consequence of the short-term stochastic parameters related to renewable production and electricity demand. The model is demonstrated through a full-scale long-term analysis of cost-efficient decarbonization of the European power system.

First we review relevant power sector models that have been used for similar studies. In particular, we focus on how they handle short-term uncertainty and short-term dynamics when modeling system operation, and long term-dynamics related to investment decisions.

DIMENSION is an optimization based dynamic investment model for the European power system, developed at the Institute of Energy Economics University of Cologne (Richter, 2011). Jägemann et al. (2013) use the DIMENSION model for an extensive analysis of the European electric power sector, establishing the cost of decarbonization in 36 cases with a wide variety of policy regulations and assumptions regarding technology availability and economic conditions. Another optimization based investment model, the LIMES-EU$^+$, is used by Haller et al. (2012) to study decarbonization of the European power sector without the use carbon capture and storage (CCS) and nuclear power. There are similarities and differences between EMPIRE and these models. The DIMENSION model and the LIMES-EU$^+$ model are dynamic models, co-optimizing investment and operation over a long time horizon. However, both these models are deterministic while EMPIRE includes short-term uncertainty.

A dynamic, multi-stage stochastic version of the DIMENSION model is presented in Fürsch et al. (2013), where investments in generation capacity are done under uncertainty about renewable energy deployments. This is an example of incorporation of long-term uncertainty, which is different from the operational uncertainty considered in EMPIRE. Operational uncertainty is included in another version the DIMENSION model published in Nagl et al. (2013). In this version investments are done facing uncertainty in solar and wind production. Although this is similar to the approach used in EMPIRE when it comes to modeling uncertainty, the model is static, using a single investment period, and can therefore not be applied to address transitional development of the European system. EMPIRE, on the other hand, includes long-term dynamics by incorporating multiple investment periods.

There are also investment models for the European power system that consider how the short-term uncertainty affects operational decisions. In the E2M2 model, see Swider and Weber (2007), system operation is modeled as a multi-stage stochastic program, with uncertainty in intermittent power production represented using a recombining tree formulation. Investments are optimized in myopic single steps, and several periods are considered sequentially. E2M2 is used by Spiecker and Weber (2014) to analyze five policy story lines for emission reduction in Europe, with a focus on cost and technology mix development. Jaehnert et al. (2013) present a capacity expansion model based on the power market simulator EMPS, which is extended to incorporate endogenous investment decisions. EMPS is a stochastic dynamic programming model originally designed for power market analysis of hydro- dominated systems, and is used extensively for management of reservoirs for hydroelectric generation under uncertain inflow and market conditions (Wolfgang et al., 2009). Similarly to the E2M2 model, investments in the extended EMPS model are myopic for single steps. There are two important distinctions between EMPIRE and these two models. The E2M2 and EMPS models have sophisticated operational modeling, but investments are myopic. In EMPIRE all investment periods are included in a single optimization, but the details in the operational modeling is reduced for the model to remain tractable. Short-term uncertainty is considered, but only when investments are made. Operational decisions are made under (short-term) perfect foresight.

Seljom and Tomasgard (2015) discuss a methodology for including short-term uncertainty in the energy system investment framework TIMES. Similarly to EMPIRE short-term and long-term dynamics are considered. The resulting model is presented as a two-stage stochastic program with investment decisions as first stage variables and operational decisions as second stage variables. Essentially this approach is equivalent to the multi-horizon tree formulation used in EMPIRE, as here-and-now short-term decisions are decoupled from future decisions.

Our work extends the body of modeling work already done on the topic of decarbonization of European power. The methodological contribution in this paper is the description of the capacity expansion model EMPIRE which includes

1. long-term dynamics: multiple investment periods
2. short-term dynamics: multiple sequential operational decision periods and market clearing
3. short-term uncertainty: multiple scenarios for input data describing operating conditions (wind, solar and load profiles, hydro power production limits, etc.)

While the full mathematical description of EMPIRE has not been published, previous versions of the model have been used to assess implications of global climate mitigation strategies for the European power system, see Skar et al. (2014), and for several studies of CCS deployment in Europe organized by Zero Emissions Platform (ZEP, 2013, 2014, 2015).

The structure of the paper is as follows: Section 2 presents EMPIRE, its design, mathematical formulation and a stochastic scenario generation routine. Section 3 presents a case study of European power decarbonization using the EU 2013 reference case data EC (2014).[1] Following the analysis, the final section presents the conclusions of the study. Lastly, a list of symbols used in the mathematical description of EMPIRE, and a discussion on input data sources and preprocessing are included in appendices at the end.

2 Approach

The European Model for Power System Investment with (high shares of) Renewable Energy (EMPIRE) is a capacity expansion model designed to assess optimal capacity investments and system operation over medium to long-term planning horizons, typically ranging 40–50 years. A total of 31 European countries are included in the model, connected through 55 interconnectors, as depicted in Figure 1. Following the tradition of recently developed models with similar scope, a central planner perspective is used, minimizing a system costs objective while serving a price inelastic demand (see Jägemann et al. (2013); Nagl et al. (2013); Spiecker and Weber (2014); Haller et al. (2012)). This is equivalent to an economic social surplus maximization, a commonly used model of perfectly competitive markets, with consumer decisions fixed ex ante. These types of models are often referred to as power market models, and are frequently in use for studying policy and regulation in the liberalized European power sector.

[1] In order to avoid confusion over the use of the word *scenario* (in this paper used for stochastic scenarios) we label the input data from EC (2014) as the *EU reference case 2013* rather than the actual name used by the European Commission, namely EU (energy, transport and GHG emissions trends to 2050) reference scenario 2013.

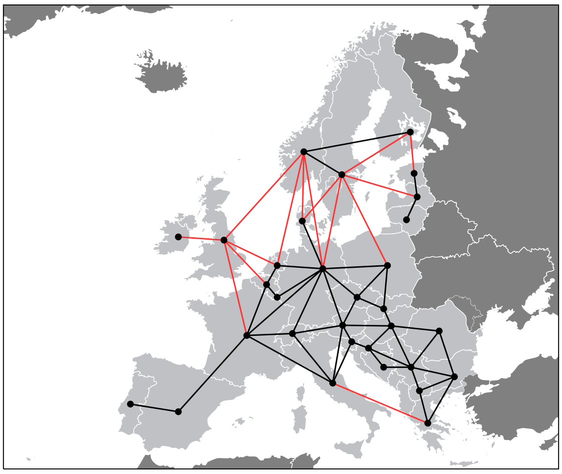


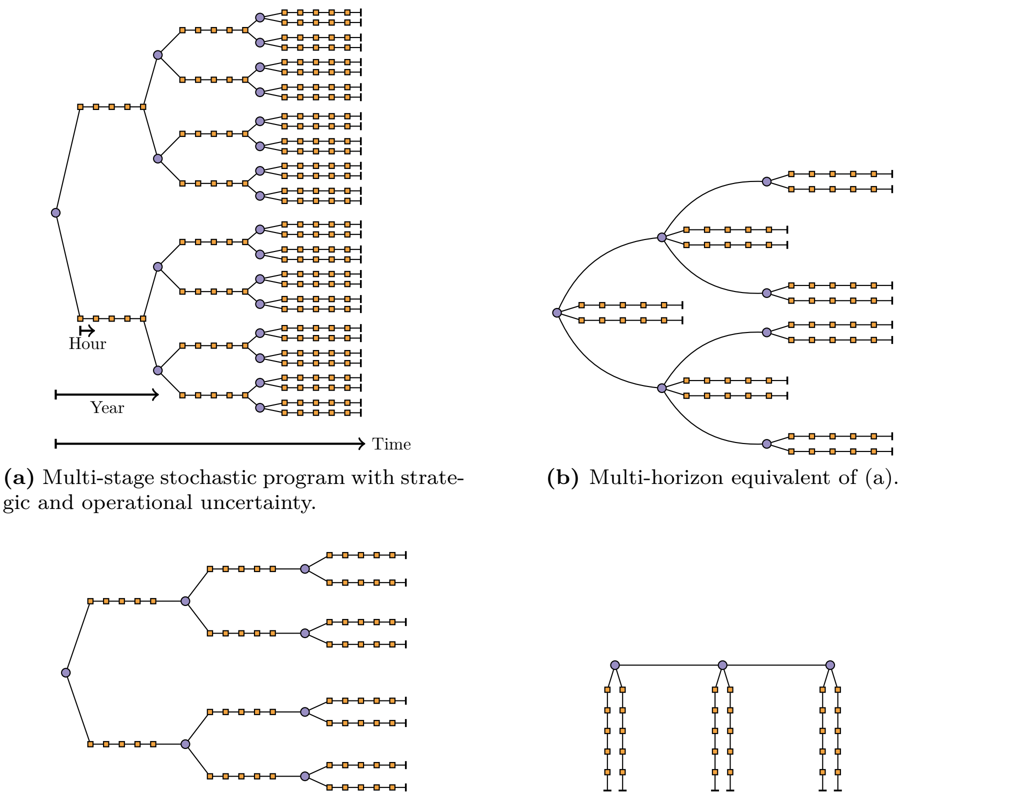
Figure 1: Spatial detail of the EMPIRE model. The coverage include all the nationalities represented in the ENTSO-E (as of 2010), except Cyprus, Iceland and Montenegro. This coincide with the EU-28 (less Cyprus and Montenegro) plus Bosnia Herzegovina, Norway, Serbia and Switzerland. As the expansion cost of high voltage (HV) cables are higher than for HV lines, these are identified using a red color in this figure.

2.1 EMPIRE modeling structure

2.1.1 Multi-horizon tree formulation

The effect of short-term uncertainty about the system operating conditions on investment decision is captured by formulating EMPIRE as a stochastic programming model (Birge and Louveaux, 2011). Although, owing to its dynamic formulation, EMPIRE could have been cast as a standard multi-stage stochastic program, an alternative, approximate, formulation is applied. The methodology used is based on the principles of multi-horizon stochastic programming, as presented by Kaut et al. (2014). This is a framework for stochastic models exhibiting two time-scales for decisions and uncertainty, referred to as respectively long-term (strategic) and short-term (operational). As a precondition the strategic and operational uncertainty have to be represented by independent stochastic processes. The operational decisions are associated with a particular strategic stage, and the strategic decisions are made subject to operational uncertainty. However, it is assumed that current operational decisions, and the information learned from observing realized operational uncertainty, do not affect future strategic or operational decisions. Following this logic, it is possible to isolate current operational decisions from future decisions. Each strategic node will then have embedded operational nodes (which may incorporate further uncertainty, making it a sub-tree), however, there are no branches connecting operational nodes to future strategic nodes. This greatly reduces the total size of the tree. Figure 2 shows examples of full multi-stage stochastic programming problems and their reduced multi-horizon representation. Following the notation in Kaut et al. (2014) we let circles represent investment (strategic) decision stages (●) while squares represent operational decisions stages (■). Termination of a branch, in the sense that no future stages are directly linked to a given node is indicated by a line ($\perp$).

Stochastic energy system investment models naturally lend themselves to this classification, as both long-term investment decisions and short-term operational decisions are co-optimized. For power system models, typical strategic uncertainty may include long-term development in



(a) Multi-stage stochastic program with strategic and operational uncertainty.

(b) Multi-horizon equivalent of (a).

(c) Multi-stage stochastic program without strategic uncertainty.

(d) Multi-horizon equivalent of (c).

Figure 2: Examples of multi-scale multi-stage stochastic trees and their multi-horizon counterparts. Typical long-term and short-term time scales are shown in (a).

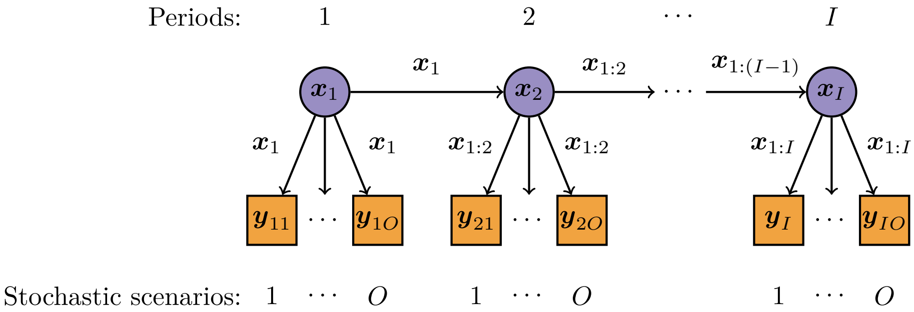


Figure 3: Temporal and stochastic scenario setup in EMPIRE. Circles indicate investment decision stages and squares indicate operational stages. Periods are indexed by the set $\mathcal{I}$ and the stochastic scenarios are collected in a finite sample space Ω.

fuel prices and energy demand, policy and regulation, investment costs and technology learning. Operational uncertainty, relates to the more short-term system dynamics: demand fluctuations, renewable energy production, short-term fuel price variability.

In the formulation of EMPIRE we have assumed perfect foresight in terms of the strategic data. The operational uncertainty is reflected in the load profiles, wind and solar generation profiles, and seasonal availability of water stored in reservoir for hydroelectric production. To simplify the exposition the same sample space $\Omega = \{1, \dots, O\}$ is used for operational scenarios in every investment period, however, it should be noted that this is not a restriction of the multi-horizon tree formulation. The structure of the decision making process is shown in Figure 3. The vectors $\boldsymbol{x}_i$ are collection of strategic (investment) decisions in period $i \in \mathcal{I} = \{1, \dots, I\}$, and $\boldsymbol{x}_{i:j}$ denotes the collection of vectors $\boldsymbol{x}_i, \boldsymbol{x}_{i+1}, \dots, \boldsymbol{x}_j$, $i, j \in \mathcal{I}$. In the operational stages, $\boldsymbol{y}_{i\omega}$ is the collection of all the operational decisions (such as generation, line flows, storage handling etc.) in period $i \in \mathcal{I}$ and stochastic scenario $\omega \in \Omega$. For each period a strategic decision is made, subject uncertainty about which operational scenario $\omega \in \Omega$ will be realized.

The prefect foresight assumption used for long-term data leads to investment decisions tailored to fit a particular future in terms of fuel prices, carbon prices, demand growth, technological development, etc. However, the investments will account for the fact that operational conditions are difficult to predict at the time of the investment. In particular, the resulting investments will not be optimized for a single set of profiles for load and intermittent renewable production, but they will be optimized across several possible outcomes.

2.1.2 Temporal aggregation

In order to reduce the problem size, and computational effort of solving the optimization problem, two types of temporal aggregation schemes have been applied. As the main interest is the long-term expansion of the system, some dynamic granularity is sacrificed by considering five year time blocks rather than annual steps for the investment periods $i \in \mathcal{I}$. Capacity investments are assumed to be available starting from the same time period as the decision is made, and payments are done upfront.

A second step of the problem size reduction is used in the computation of annual operational costs. Rather than computing the system dispatch over a full year of 8760 hours we work with a reduced set of operational hours $\mathcal{H}$. The set $\mathcal{H}$ is subdivided into seasons, indexed by a set $\mathcal{S}$. EMPIRE applies a distinction between two types of seasons, regular seasons and extreme

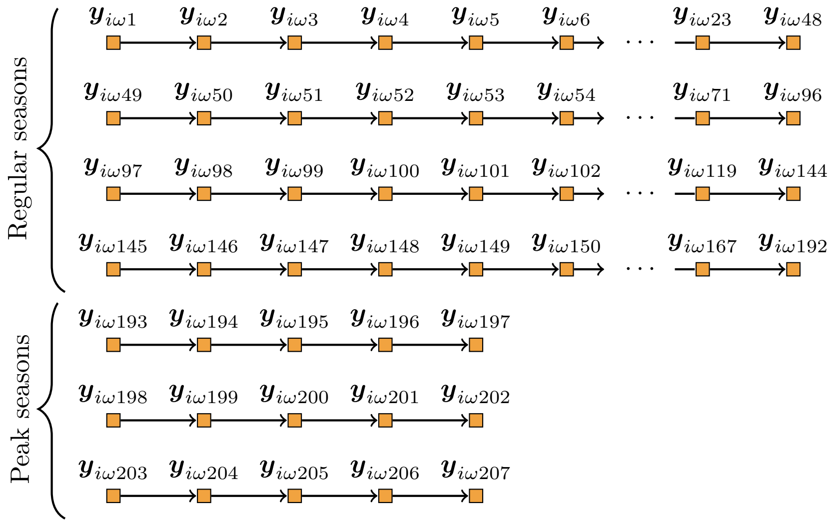


Figure 4: Illustration of the annual operation setup in EMPIRE. In this example there are four regular seasons, each with 48 consecutive hours, and three extreme load seasons, each with five consecutive hours.

load seasons, with different numbers of operational hours modeled. The extreme load seasons are assumed to cover just a small fraction of the year, but they are useful for determining the need to install back-up capacity. By including these seasons in the operational modeling, the contribution of intermittent renewables in the electricity supply during such periods can be evaluated for a number of different scenarios. An approach similar to this, albeit in a deterministic setting, was used by Haller et al. (2012), where the normal operation was modeled using four seasons, each with three days divided into four time slices of six hours. For representing constrained supply situations they included an additional time slice, assuming high load and low renewable generation.

Figure 4 illustrates the temporal connection between operational decision vectors $\{\boldsymbol{y}_{i\omega h}\}_{h\in\mathcal{H}}$ in a given period $i \in \mathcal{I}$ and stochastic scenario $\omega \in \Omega$ (the full collection correponds to $\boldsymbol{y}_{i\omega}$ in Figure 3). As a matter of convenience the elements in $\mathcal{H}$ are labeled consecutively, $\mathcal{H} = \{1, \ldots, H\}$, although two consecutive hours in $\mathcal{H}$ are only consecutive in the modeling if they belong to the same set $\mathcal{H}_s$, for a season $s \in \mathcal{S}$.

A routine for scenario generation used to structure the operational data, as shown in Figure 4, has been created specifically for EMPIRE. This is documented in Section 2.3.

2.2 Mathematical formulation

In the following a complete description of the mathematical formulation of EMPIRE is provided, focusing on how the equations describe the investment and operation decision process. The actual implementation of EMPIRE is done using the Xpress-Mosel environment of the FICO® Xpress Optimization Suite (Heipcke, 2012; FICO®, 2015).

2.2.1 Objective function

The objective in EMPIRE is to minimize the sum of investment and (expected) operational costs for the system as whole, over all time periods in $\mathcal{I}$, discounted at rate r. Capacity investments are possible for generators $g \in \mathcal{G}$, denoted by decision variable x_{gi}^{gen}, and interconnectors $l \in \mathcal{L}$, denoted by x_{li}^{tran}. Storages, $b \in \mathcal{B}$, are modeled by a power (charge/discharge) capacity and an energy storage capacity, for which the investment decision variables are denoted by x_{bi}^{storPW} and x_{bi}^{storEN}, respectively. The investment costs are assumed linear as a function of the investment size for all assets, and the cost coefficients are given by c_{gi}^{gen} for generators, and by c_{li}^{tran} for interconnectors. For storages the power and energy investment costs are denoted by c_{bi}^{storPW} and c_{bi}^{storEN}. The investment cost parameters include capital costs, and fixed operation and maintenance costs, paid over the lifetime of an asset. For assets with life times expiring beyond the analysis horizon given by $\mathcal{I}$, the investment cost parameters are adjusted to account for salvage value.

In the expression for system operational costs, the model assumes linear production cost profiles for all generators. For a dispatch hour $h \in \mathcal{H}$, in period $i \in \mathcal{I}$ and stochastic scenario $\omega \in \Omega$, the decision variables describing generator production output are denoted by $y_{ghi\omega}^{\text{gen}}$, for $g \in \mathcal{G}$. The production cost coefficients, q_{gi}^{gen}, reflect all variable costs: fuel costs, carbon emission costs, operation and maintenance costs, and carbon capture and storage costs. These interpreted as short-run marginal costs (SRMC) due to the linear formulation. At every node $n \in \mathcal{N}$ the model has the ability to reduce load if it cannot be met by other means such as generation, import or storage discharge. The cost of load shedding is given by the product of the load shedding amount, $y_{nhi\omega}^{\text{ll}}$, and the value of lost load (voll), denoted by q_{ni}^{ll}.

The objective function is formulated as

$$\begin{aligned}\min_{\boldsymbol{x}, \{\boldsymbol{y}_\omega\}_{\omega\in\Omega}} z = & \sum_{i\in\mathcal{I}} (1+r)^{-5(i-1)} \times \\ & \Bigg\{ \underbrace{\sum_{g\in\mathcal{G}} c_{gi}^{\text{gen}} x_{gi}^{\text{gen}} + \sum_{l\in\mathcal{L}} c_{li}^{\text{tran}} x_{li}^{\text{tran}} + \sum_{b\in\mathcal{B}} \left(c_{bi}^{\text{storPW}} x_{bi}^{\text{storPW}} + c_{bi}^{\text{storEN}} x_{bi}^{\text{storEN}} \right)}_{\text{Investment cost for generation, transmission and storage capacity, period } i} \\ & + \vartheta \sum_{\omega\in\Omega} \pi_\omega \sum_{s\in\mathcal{S}} \alpha_s \sum_{h\in\mathcal{H}_s} \underbrace{\sum_{n\in\mathcal{N}} \Big[\sum_{g\in\mathcal{G}_n} \left(q_{gi}^{\text{gen}} y_{ghi\omega}^{\text{gen}} \right) + q_{ni}^{\text{ll}} y_{nhi\omega}^{\text{ll}} \Big]}_{\substack{\text{System operation cost (all nodes } n\text{),} \\ \text{generation + value of lost load,} \\ \text{period } i\text{, scenario } \omega\text{, season } s\text{, hour } h}} \Bigg\}. \end{aligned} \tag{1}$$

The collection $\{\pi_\omega\}_{\omega\in\Omega}$ comprises discrete probabilities on the finite sample space Ω, which makes the sum of operational costs over all $\omega \in \Omega$ scaled with π_ω an expected value.

In order to account for problem size reduction, as discussed in the previous section, we use scaling factors to ensure that investment and operational costs have the same temporal resolution. The factor ϑ is a five year inverse capital recovery factor,[2] scaling annual values to a five year value, a necessity due to the use of five year block periods $i \in \mathcal{I}$. The scaling factors α_s, for season $s \in \mathcal{S}$, account the contribution parameters and variables in different seasons have to an annual figure. As an example, suppose that we define the total generation in season $s \in \mathcal{S}$, period $i \in \mathcal{I}$ and stochastic scenario $\omega \in \Omega$ as $Y_{si\omega}^{\text{gen}} = \sum_{h\in\mathcal{H}_s} \sum_{g\in\mathcal{G}} y_{ghi\omega}^{\text{gen}}$. Then $Y_{i\omega}^{\text{gen}} = \sum_{s\in\mathcal{S}} \alpha_s Y_{si\omega}^{\text{gen}}$

[2] $\vartheta = \sum_{j=0}^{4} (1+r)^{-j} = \frac{(1+r)^5 - 1}{r(1+r)^4}$

is the total annual generation in period i, scenario ω. The expected annual generation in period i is $Y_i^{\text{gen}} = \sum_{\omega \in \Omega} \pi_\omega Y_{i\omega}^{\text{gen}}$.

2.2.2 Dispatch model

The system operation is governed by a number of energy balance constraints, one for every node and every dispatch hour considered, and a number of technical constraints for the generators and interconnector links between nodes. The collection of all of the following constrains for a period $i \in \mathcal{I}$ and stochastic scenario $\omega \in \Omega$ define the annual dispatch of the system.

For every hour, $h \in \mathcal{H}$, the sum of net local generation and net import is required to balance the load at every node, $n \in \mathcal{N}$, denoted by the parameter $\xi_{nhi\omega}^{\text{load}}$. We let $y_{ahi\omega}^{\text{flow}}$ be the unidirectional flow on an arc connecting node n to a neighboring node in the network (see Figure 1). For each node the sets $\mathcal{A}_n^{\text{in}}$ and $\mathcal{A}_n^{\text{out}}$ contains the arcs going into, or out from, node n, respectively. Transmission losses are accounted for at the importing node, by down-scaling the flows for arcs $a \in \mathcal{A}_n^{\text{in}}$ by efficiency parameters η_a^{tran}, where $\eta_a^{\text{tran}} \in (0,1)$. The decision variables $y_{bhi\omega}^{\text{chrg}}$ and $y_{bhi\omega}^{\text{dischrg}}$ denote storage charging and discharging variables, and η_b^{dischrg} the discharge efficiency ($\eta_b^{\text{dischrg}} \in (0,1)$). The sets $\mathcal{G}_n$ and $\mathcal{B}_n$ contain the generators and energy storages, respectively, which are located at node n. The single hour node load balance, or dispatch, constraint is formulated as

$$\underbrace{\sum_{g \in \mathcal{G}_n} y_{ghi\omega}^{\text{gen}}}_{\text{Generation}} + \underbrace{\sum_{b \in \mathcal{B}_n} \eta_b^{\text{dischrg}} y_{bhi\omega}^{\text{dischrg}} - y_{bhi\omega}^{\text{chrg}}}_{\text{Storage handeling}} + \underbrace{\sum_{a \in \mathcal{A}_n^{\text{in}}} \eta_a^{\text{tran}} y_{ahi\omega}^{\text{flow}} - \sum_{a \in \mathcal{A}_n^{\text{out}}} y_{ahi\omega}^{\text{flow}}}_{\text{Net import}} = \xi_{nhi\omega}^{\text{load}} - y_{nhi\omega}^{\text{ll}},$$
$$n \in \mathcal{N}, h \in \mathcal{H}, i \in \mathcal{I}, \omega \in \Omega.$$

The nodal load is by this design price insensitive, apart from in highly constrained supply situations when load can be shed at the cost of value of lost load. The shadow prices of the node load balance constraints are reported as power prices. Uncertainty in the load profiles is introduced by using unique input data for every $\omega \in \Omega$.

Every generator, interconnector and storage (power and energy) have rated maximum installed capacities, v_{*i}^{**}, which for every period $i \in \mathcal{I}$ are given by the initial capacity still in operation, $\overline{x}_{*i}^{**}$, and cumulative investments which have not expired their lifetime, i_*^{life}.[3] Asterisks $**$ are used to indicate type of capacity (generator, line, storage power or storage energy) and $*$ indicate the element in the set of all objects of the given type (e.g. $g \in \mathcal{G}$ for generators), allowing for a generic definition of capacity. This is given as

$$v_{*i}^{**} = \overline{x}_{*i}^{**} + \sum_{j=i'}^{i} x_{*j}^{**}, \quad i' = \max\{1, i - \lfloor i_*^{\text{life}}/5 \rfloor\}, i \in \mathcal{I}.$$

Vintage and new capacities are aggregated as we consider each generator, interconnector and storage to represent the installed capacity for a given period $i \in \mathcal{I}$. For thermal and hydro generators, $g \in \mathcal{G}^{\text{Thermal}} \cup G^{\text{Hydro}}$, v_{gi}^{gen} is the total installed capacity of a technology at a given node. As an example, nuclear power in France is considered one generator. Pooling generation resources this way reduces the number of decision variables in the dispatch problems, however, the trade-off is that the model cannot keep track of the age distribution of a technology when

[3]The investment life time parameters are given in years, while the periods $i \in \mathcal{I}$ represents five year time blocks. When determining if an asset is active in period i the life time parameters must be divided by 5. The $\lfloor \cdot \rfloor$ notation is used for the floor operator.

computing the optimal dispatch. As a result, if a technology is improved from one investment period to the next, the improvement is applied to the entire power plant fleet of that technology. Wind and solar generators are not aggregated by technology in the same way, but represents locations within a country with different production resource potentials.

Production from each generator for a dispatch hour is limited by the available installed capacity. We use availability parameters, $\xi^{\text{gen}}_{ghi\omega}$, where $\xi^{\text{gen}}_{ghi\omega} \in (0,1)$, to derate the installed capacity for generator $g \in \mathcal{G}$ in hour $h \in \mathcal{H}$. The maximum production constraint is then

$$y^{\text{gen}}_{ghi\omega} \leq \xi^{\text{gen}}_{ghi\omega} v^{\text{gen}}_{gi}, \quad g \in \mathcal{G}, h \in \mathcal{H}, i \in \mathcal{I}, \omega \in \Omega,$$

For intermittent production, such as wind power and solar power, the availability parameters are stochastic and represented by scenario dependent normalized production profiles. These profiles have an hourly scale, and the data used is generated by the routine described in Section 2.3. As for the load parameters, the intermittent production profiles are unique for each stochastic scenario $\omega \in \Omega$, reflecting the operational uncertainty experienced at the time of investment. For thermal generators the availability parameters are constant across all hours $h \in \mathcal{H}$, and are based on average capacity factors for the given technologies.

Ramp up of production for thermal generators, $g \in \mathcal{G}^{\text{Thermal}}$, is assumed to be limited to a certain share of the installed capacity, given by the parameter γ^{gen}_g, where $\gamma^{\text{gen}}_g \in (0,1)$. The ramping constraints are formulated as

$$y^{\text{gen}}_{ghi\omega} - y^{\text{gen}}_{g(h-1)i\omega} \leq \gamma^{\text{gen}}_g v^{\text{gen}}_{gi}, \quad g \in \mathcal{G}^{\text{Thermal}}, s \in \mathcal{S}, h \in \mathcal{H}^-_s, i \in \mathcal{I}, \omega \in \Omega.$$

The decision variables $w^{\text{stor}}_{bhi\omega}$ keep track of the energy level for storage $b \in \mathcal{B}$. At every hour (except the first in a season), the storage end-level is set as the difference between the energy level in the previous hour minus the net discharge. The storage energy-balance constraint is given as

$$w^{\text{stor}}_{b(h-1)i\omega} + \eta^{\text{chrg}}_b y^{\text{chrg}}_{bhi\omega} - y^{\text{dischrg}}_{bhi\omega} = w^{\text{stor}}_{bhi\omega}, \quad b \in \mathcal{B}, s \in \mathcal{S}, h \in \mathcal{H}^-_s, i \in \mathcal{I}, \omega \in \Omega.$$

Losses are attributed both to the charging and discharging of the energy storage, and the round-trip efficiency is given as $\eta^{\text{roundtrip}}_b = \eta^{\text{chrg}}_b \eta^{\text{dischrg}}_b$. The stored energy and charging/discharging are limited by the energy and power installed capacities, given by

$$w^{\text{stor}}_{bhi\omega} \leq v^{\text{storEN}}_{bi}, \quad y^{\text{chrg}}_{bhi\omega} \leq v^{\text{storPW}}_{bi}, \quad y^{\text{dischrg}}_{bhi\omega} \leq \rho_b v^{\text{storPW}}_{bi},$$
$$b \in \mathcal{B}, h \in \mathcal{H}, i \in \mathcal{I}, \omega \in \Omega.$$

The (non-negative) parameter ρ_b determines a fixed discharge to charge power capacity ratio and allows for specifications of storage technologies where the maximum charging power can be different from the maximum discharge power.

Hydroelectric power generation is modeled with low variable operational cost, but constrains are imposed on the hydro operation to account for water availability in reservoirs and hydro-electric resource potential. For regulated hydroelectric generators, $g \in G^{\text{RegHydro}}$, energy limits given by $\xi^{\text{RegHydroLim}}_{gsi\omega}$, constrain the total production over each season. The constraint is given by

$$\sum_{h \in \mathcal{H}_s} y^{\text{gen}}_{ghi\omega} \leq \xi^{\text{RegHydroLim}}_{gsi\omega}, \; g \in \mathcal{G}^{\text{RegHydro}}, s \in \mathcal{S}, i \in \mathcal{I}, \omega \in \Omega. \tag{2}$$

For every node, the total hydroelectric generation, both regulated and unregulated, is limited in terms of annual energy production

$$\sum_{s \in \mathcal{S}} \alpha_s \times \sum_{h \in \mathcal{H}_s} \sum_{g \in \mathcal{G}^{\text{Hydro}}_n} y^{\text{gen}}_{ghi\omega} \leq \xi^{\text{HydroLim}}_{ni\omega}, \; n \in \mathcal{N}, i \in \mathcal{I}, \omega \in \Omega. \tag{3}$$

The hydroelectric energy limits also depend on the stochastic scenarios, allowing EMPIRE to reflect uncertainty about water availability for power production.

EMPIRE has a simplified network description, only considering import/export links between countries (resembling a net transfer capacity, NTC, representation). Exchange is limited by the (symmetric) capacity for each interconnector, $l \in \mathcal{L}$, given as

$$y^{\text{flow}}_{ahi\omega} \leq v^{\text{tran}}_{li}, \quad l \in \mathcal{L}, a \in \mathcal{A}_l, h \in \mathcal{H}, i \in \mathcal{I}, \omega \in \Omega. \tag{4}$$

The sets $\mathcal{A}_l$ contains the pair of unidirectional arcs which together represents the flow across interconnector l. According to this formulation the exchange between countries is fully controllable within capacity limits, an assumption leading to an overestimation of the network flexibility. In reality, flows in an electric network are determined by physical laws, the network characteristics, and power injections and withdrawals. By neglecting this fact, the dispatch found by the model may result in flows that would deviate significantly from actual flows in an electric network (even violate security constraints), commonly referred to as loop flows. However, this simplification reduces both the data requirements for the gird specification and the computational burden of solving the optimization problem and is commonly used in similar studies (Jägemann et al., 2013; Spiecker and Weber, 2014; Haller et al., 2012).

2.2.3 Capacity investment constraints

There are two types of constraints on generation capacity investments in EMPIRE: limits on possible investments per period for a given technology in a given node, and maximum installed capacity constraints. Their formulations are given in equations (5) and (6), respectively.

$$\sum_{g \in \mathcal{G}_{tn}} x^{\text{gen}}_{gi} \leq \overline{X}^{\text{gen}}_{ti}, \quad t \in \mathcal{T}^{\text{AggTech}}, n \in \mathcal{N}, i \in \mathcal{I}, \tag{5}$$

$$\sum_{g \in \mathcal{G}_{tn}} v^{\text{gen}}_{gi} \leq \overline{V}^{\text{gen}}_{tni}, \quad t \in \mathcal{T}^{\text{AggTech}}, n \in \mathcal{N}, i \in \mathcal{I}. \tag{6}$$

The capacity constraints are given at an aggregate technology level per node, rather than a generator level. The limits encompass a combination of technical, economic, environmental or regulatory constraints, some of which are clearly stated policies, like the Germany nuclear power moratorium from 2022, while others are more intangible, such as a limits on wind power expansion in a given country, or opposition against coal-fired power generation.

Similar constraints to Eq. (5) and (6) are imposed for lines and storages (power and energy) capacity investments and installed capacities (omitted here for brevity). The power and energy capacity investments for storages are sized independently unless additional constraints are imposed. For some storage technologies, such as batteries,[4] we fix one of the quantities as a function of the other by imposing the following constraint for a subset of storages $\mathcal{B}^{\dagger}$,

$$v^{\text{storPW}}_{bi} - \beta_b v^{\text{storEN}}_{bi} = 0, \quad b \in \mathcal{B}^{\dagger}, i \in \mathcal{I}.$$

The parameters β_b is the fixed storage power to energy ratio.

[4]The coupling between power and energy capacity vary significantly between different energy storage technologies. For pumped-hydro the energy capacity is given by the size and design of the upstream (and possibly downstream) reservoir(s), while the power capacity is for the most part determined by the power generation equipment. Modern utility grade batteries, on the other hand, are delivered as units with pre-specified power and energy capacities determined by the technology and electronics used in the design.

2.3 Stochastic scenario generation routine

A scenario generation routine was developed to construct hourly data series to be used in the EMPIRE operational modeling, as shown in Figure 4. For this purpose multi-annual hourly profiles for load, (onshore/offshore) wind power production and solar photovoltaics (PV) production were collected. Hourly profiles for regulated hydroelectric power production were synthesized using a specialized routine.

In order to preserve auto-correlation and correlation between data series, it was decided that the data used for the scenarios $\omega \in \Omega$ would come from a sample of consecutive hours from historical data, and that, within a scenario, the same hours would be used for all the data series. The samples would be randomly chosen, so that

- each scenario would generally get different data, and
- on average, the mean and variance of the sampled data would match that of the original series.

The following explains the implementation of the scenario generation routine.

The first step involves preparing the raw data series. Let $\{\tau^{\text{type}}_{*hk}\}_{h\in H^{\text{full}},k\in\mathcal{K}}$ be the annual hourly data profile for a given parameter type (e.g. load, wind, solar PV and hydro profiles) for a number of historic years indexed by a set $\mathcal{K}$. The first index of τ^{type}_{*hk} is an object identifier which relates to the type of the profile. For load series, this index identifies the node, for wind production data it identifies a particular generator. A wild-card sign is used when the data series type is not indicated. The set H^{full} is simply the range $[1, 8760]$, i.e. all hours in a full year, meaning that leap year data is disregarded. Before applying the scenario generation scheme a data pre-processing was conducted:

1. If there are missing observations in any of the data series, these are re-constructed by either linear interpolation between the closest available hours, or replicating those values in case the missing observations are at the beginning or the end of the respective series.
2. Make an ordered partition of the set of indices H^{full} into four season sets $H^{\text{full}} = \{H^{\text{full}}_1, H^{\text{full}}_2, H^{\text{full}}_3, H^{\text{full}}_4\}$. The number of elements of each season is equal, i.e. $|H^{\text{full}}_s| = 2190$, for $s = 1, \dots, 4$.

The scenario generation routine is used to construct base data series $\{\xi^{\text{type}}_{*h0\omega}\}_{h\in\mathcal{H},\omega\in\Omega}$ from the historical data $\{\tau^{\text{type}}_{*hk}\}_{h\in H^{\text{full}},k\in\mathcal{K}}$. The algorithm goes as follows

For every scenario $\omega \in \Omega$

1. Select a random year $k' \in \mathcal{K}$.
2. For each regular season $s = 1, \dots, 4$
   (a) Sample a random number θ_s between 1 and $2190 - (l + 1)$, where l is the number of hours in the EMPIRE regular season
   (b) Populate the regular hours of base data series $\xi^{\text{type}}_{*h0\omega}$ by setting
   $$\xi^{\text{type}}_{*h0\omega} = \tau^{\text{type}}_{*h'k'}, \quad j = 1, \dots, l, \quad h = j + l \cdot (s - 1), \quad h' = \theta_s + (j - 1).$$
3. Form the first extreme load season by summing up the historical load for all nodes in a given hour $h \in H^{\text{full}}$, for the selected year:
   $$\tau^{\text{load}}_{hk'} = \sum_{n\in\mathcal{N}} \tau^{\text{load}}_{nhk'},$$

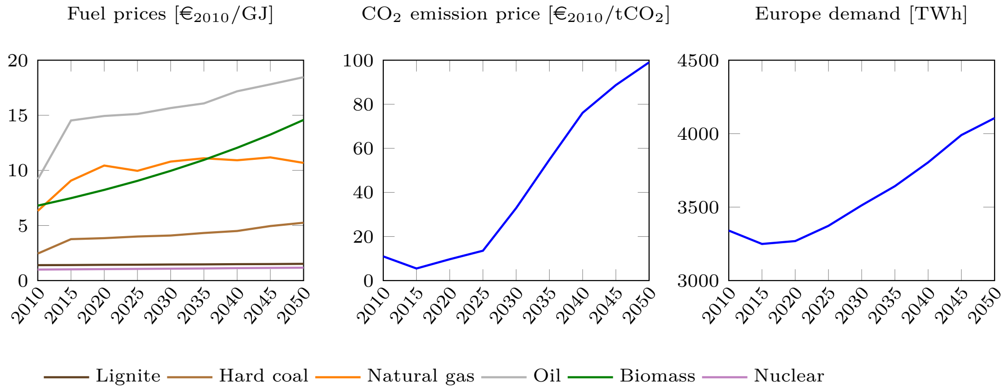


Figure 5: Fuel prices, electricity demand and carbon prices form EU 2013 Reference case. EC (2014) contains prices for hard coal, natural gas and oil. Lignite, uranium and biomass prices come from other sources, (ZEP, 2011; VGB, 2011), and are extrapolated from 2010 data.

(a) Select the hour $\overline{h}$ with the highest load value, i.e. the index $h \in H^{\text{full}}$ corresponding to the maximum element of $\{\tau^{\text{load}}_{hk'}\}_{h\in H^{\text{full}}}$.

(b) The first extreme season of $\{\xi^{\text{type}}_{*h0\omega}\}$ comprise the data from hours in the interval $[\overline{h}-2, \overline{h}+2]$ at the selected year k' of $\{\tau^{\text{type}}_{*hk}\}$.

4. Form the other extreme peak seasons by obtaining the maximum load per node

$$\tau^{\text{peakload}}_{nk'} = \max_{h\in H^{\text{full}}} \{\tau^{\text{load}}_{nhk'}\},$$

then selecting the $|\mathcal{S}^{\text{peak}}|-1$ nodes $n_1, \ldots, n_{|\mathcal{S}^{\text{peak}}|-1}$, with the highest load (where $|\mathcal{S}^{\text{peak}}|$ is the number of extreme load seasons). Extreme load season $j+1$ is formed by the hours $[\overline{h}_j - 2, \overline{h}_j + 2]$, where $\overline{h}_j$ is the hour with the highest hour load for node j.

After the procedure had been applied the sampled data profiles $\{\xi^{\text{type}}_{*h0\omega}\}$ were checked to see that they closely match the mean and variance of the respective underlying raw data series. The load and hydro base data profiles were further processed as described in the Appendix B.2.

3 EU reference scenario case study using EMPIRE

The use of EMPIRE in a decarbonization study for the European power system is illustrated on a data set based on the EU reference case 2013 recently published by the European Commission (EC, 2014). This data set establishes the conditions for the long-term dynamics of the system, such as fuel prices and electricity demand development. A climate policy, in the form of a carbon price, is also collected from the EU reference case. Some of the major assumptions are shown in Figure 5.

In this analysis we use four regular seasons, each with 48 consecutive hours, and six extreme load seasons, each with five consecutive hours. Three stochastic scenarios are used. All in all, this means that for each investment period a total of 666 dispatch hours are considered. Across all the investment periods a total of 5994 dispatch hours are used, establishing a diverse representation of different operating conditions. Appendix C provides further details regarding the input data used for this analysis.

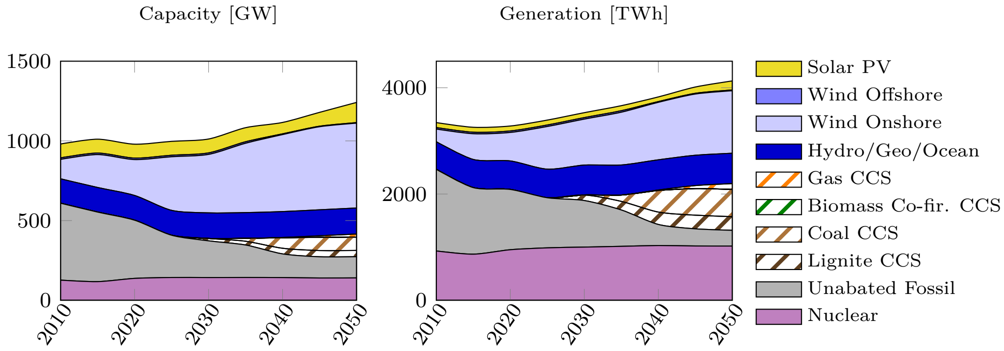


Figure 6: Optimal generation capacity and generation mix in the constrained transmission expansion case. The category Hydro/Geo/Ocean comprises aggregated results for the technologies: hydroelectric power (reservoir and run-of-the-river), geothermal energy and ocean energy. Biomass Co-fir. is a technology where 10 % biomass is cofired with hard coal.

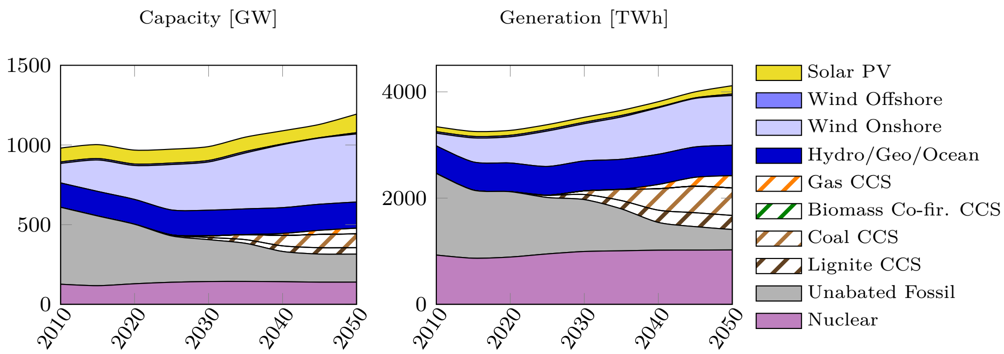


Figure 7: Optimal generation capacity and generation mix in the constrained transmission expansion case

Two transmission investment cases were developed for the purpose of this study. In the first case maximum capacities for HV line interconnectors were limited to two times their initial capacity, plus an additional 1000 MW per interconnector. By basing the maximum limit on installed capacity, a degree of inertia is introduced in the infrastructure planning, while the 1000 MW addition allows for moderate development of transmission corridors which are not of significant capacity today. For each HV cable interconnector the total expansion was limited to 1400 MW. For every time period the expansion for each HV line interconnector was limited to 10 % of the initial capacity plus 300 MW. For HV cable interconnectors the limit was set to 700 MW per time period. In the second case we did not allow for interconnector expansion.

The following sections presents the results from the two cases, and a discussion.

3.1 Aggregated results for Europe

The European generation capacity and energy mixes for the EU reference case 2013 are displayed in Figure 6 (with interconnector expansion) and Figure 7 (no transmission expansion). At an European level the differences are not tremendous, but some distinctions are worth pointing out. For onshore wind the installed capacity in 2050 is close to 530 GW in the case with

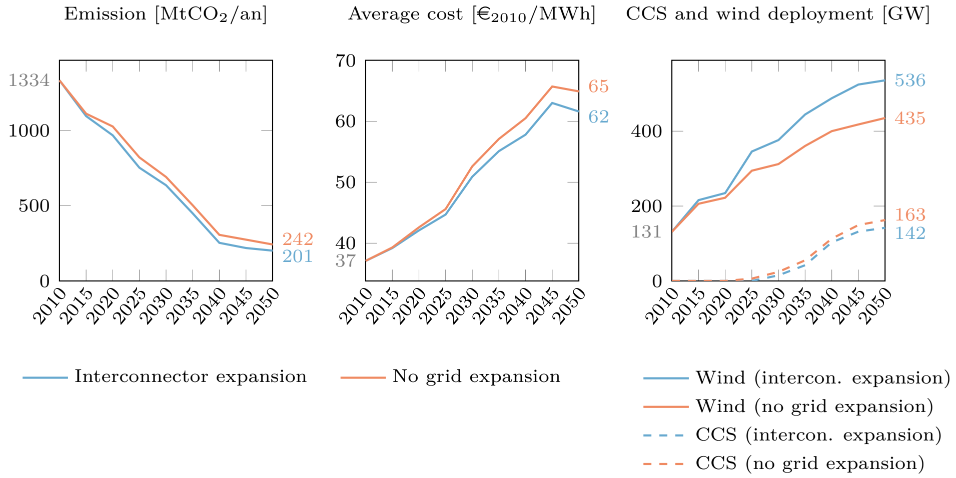


Figure 8: Emissions, average electricity cost and deployment of CCS and wind (onshore/offshore) capacities for the cases with and without interconnector expansion.

interconnector capacity expansion, about 100 GW higher than in the no expansion case. For solar PV the installed capacity in 2050 is 127 GW in the interconnector expansion case, compared to 117 GW in the no expansion. The additional renewable capacity seen in the interconnector expansion case reduces the need for thermal generation investments. For the no expansion case, unabated and CCS equipped fossil fuel generation capacities are, respectively, 43 GW and 21 GW higher than for the grid expansion case. In the energy mix for the no expansion case, this results in 88 TWh additional generation from unabated fossil generation technologies and 134 TWh more generation from CCS plants. This is offset by 171 TWh onshore wind and some additional generation from other renewables in the interconnector expansion case.

Figure 8 shows the total emissions, average cost of electricity and deployment of CCS and wind generation capacities in Europe. The two cases start to diverge from 2020. Even before the most significant differences in wind investment emerge, there is a gap between the emission trajectories for the two cases. This can be attributed to better utilization of the low-carbon generation capacities as more generation resources can be shared throughout the system. The impact of the increased levels of wind investments is seen to be larger for the average cost. An investigation of the different components of the system costs reveal that the difference is caused by a lower fuel cost in the interconnector expansion case. This is to be expected as wind generation has zero fuel costs. For the CCS capacity the differences between the cases are not considerable, however, the first CCS deployment is delayed by five years, until 2030, in the interconnector expansion case.

3.2 Interconnector expansion

The initial transmission system design and the installed interconnector capacities in the expansion case are shown in Figure 9. In the initial system the total capacity was 67 GW, while the additional interconnector expansion by 2050 ended up at 96 GW, yielding a total of 163 GW capacity for all the interconnectors (we assume no decommissioning of the existing capacities). The constraints imposed on the expansion turn out to be binding for a majority of the connections. A total of 38 out of 55 interconnectors reach the maximum install limit. In particular, all the HV

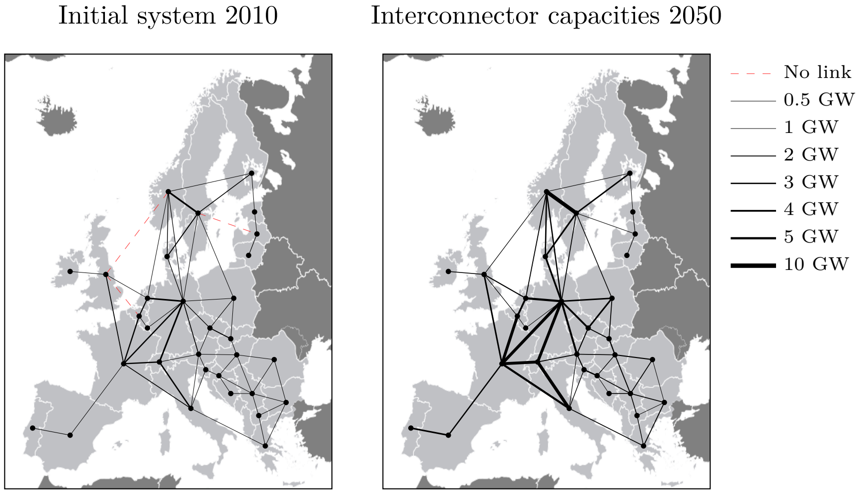


Figure 9: The initial (2010) interconnector capacities and the installed capacities in 2050.

cables links from Norway and Sweden are expanded to the maximum level. The same applies for the HV cables going from the UK to France, Belgium and the Netherlands. The connections along the south-to-north axis going from Spain through France to Germany were also develop to the maximum extent.

Most of the interconnectors with non-binding maximum expansion constraints are found in Eastern Europe and the Balkans. In addition, the links between Germany and Austria, Germany and Switzerland, and Germany and the Netherlands see non-binding constraints.

3.3 Generation capacities and energy mix by country

Figures 10 and 11 show the 2050 generation and energy mixes, in the two cases, for the ten countries with the highest electricity demand in Europe. The two cases are generally quite similar. In Germany there is a diverse mix of onshore wind (roughly 50 % of the generation capacity and 20 % of the generation mix) and fossil fueled generation, both with and without CCS. In the generation mix CCS accounts for more than half the total energy produced. In France, nuclear power and onshore wind make up more than 70 % of both the capacity and energy mix. Also, Italy, Great Britain and Spain see significant onshore wind deployment by 2050. In Germany, Italy and Great Britain the maximum install constraints on onshore wind capacity are binding in 2050. In Great Britain and Poland unabated coal and lignite generation are displaced by CCS generation. Significant amounts of natural gas fired CCGTs are used in Germany, Italy, Great Britain, Spain and Belgium.

When it comes to the differences between the two transmission expansion cases the most notable countries are France, Poland and Norway. An additional 40 GW of onshore wind is deployed in France, and 20 GW additional capacity is installed in both Poland and Norway, in the interconnector expansion case. For solar PV the additional capacity in the interconnector expansion case is installed in France (6 GW), Italy (6 GW) and Spain (4 GW), while 5 GW is reduced elsewhere in Europe yielding a net increase of a bit more than 10 GW. The reduces amount of thermal generation capacity in the no expansion case over the alternative is distributed fairly evenly across all countries.

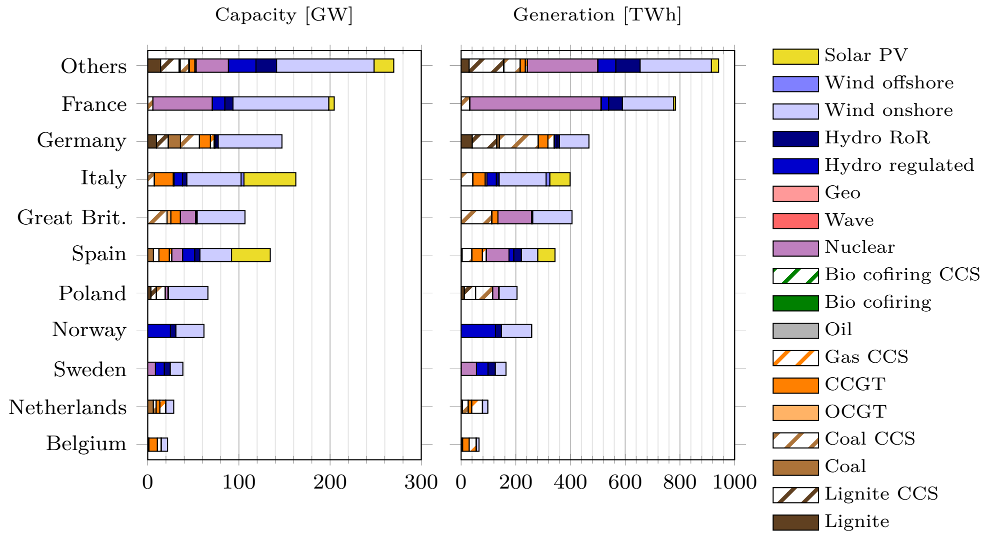


Figure 10: Transmission capacity expansion case: Country-wise Baseline scenario result generation capacity and generation mix in 2050.

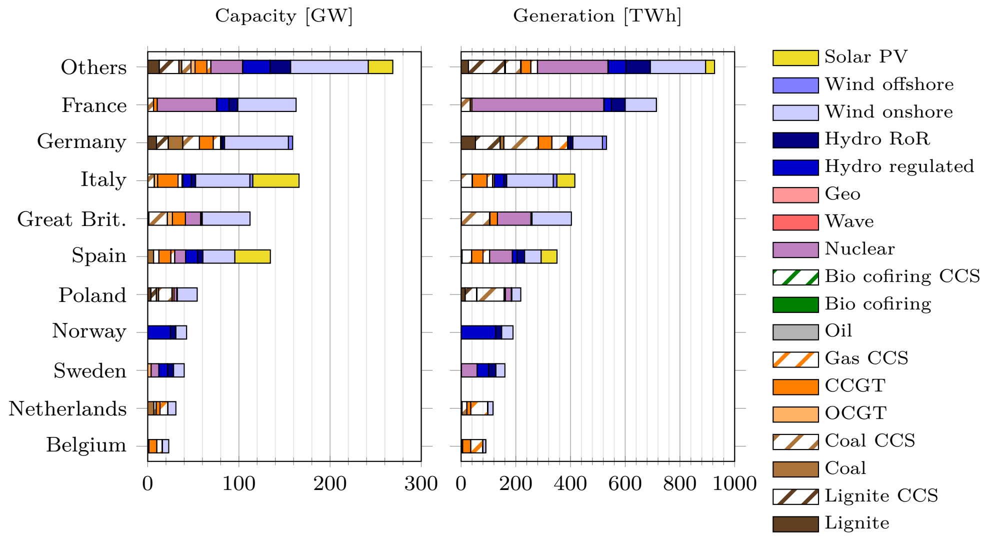


Figure 11: No transmission capacity case: Country-wise Baseline scenario result generation capacity and generation mix in 2050.

3.4 Discussion

Firstly, even with the current interconnector capacities installed in Europe there is a significant potential for large-scale deployment of onshore wind. The results show a 25 % share in the generation mix for onshore wind without grid investments, and close to 30 % in for the case with. It should be noted that the optimal interconnector expansion found, represents substantial infrastructure investments, an increase of almost 150 % on top of today's system. For solar PV, on the other hand, the effect of increased exchange capacity was modest. This implies that capital cost reductions are more important for solar deployment than grid investments.

Relative to 2010 levels, emissions are reduced by 85 % in the interconnector expansion case and an 82 % reduction in the no expansion case. Without the ability to increase interconnector capacities more CCS is deployed which essentially leads to more or less the same emission reduction. In terms of costs, however, the differences turned out to be larger. As more wind generation is deployed, accompanied by transmission expansion, less costs are incurred on fuel and carbon. The capital costs are higher, but operational cost savings are high enough to lead to a 5 % net reduction in average cost by 2050, over the no expansion case.

The constraints imposed on maximum investments in generation and transmission capacities turn out to significantly affect the resulting system design. In the case without transmission expansion five of the ten countries with highest demand for electricity experience that the maximum constraints on onshore wind expansion are binding. For the grid infrastructure a majority of the constraints placed on interconnector expansion turned out to be binding. This means that higher investments for both wind and interconnectors would likely have resulted from relaxing these constraints. It can be difficult to determine the appropriate limits to use on investments, however carefully considerations should be used as the results are clearly sensitive to these parameters.

4 Conclusions and further work

This paper provides a full methodological description of EMPIRE, a stochastic investment model for the European power system. The model features multiple investment periods, hourly dispatch modeling for selected time segments of a year and multiple stochastic scenarios representing operational uncertainty. This allows for simultaneous consideration of long-term dynamics, short-term dynamics and short-term uncertainty affecting investment decision and system operation. These are all features which are particularly important when analyzing cases with high penetrations of intermittent renewables as such technologies introduce a great deal of variability and uncertainty in the electricity supply. Computational tractability is achieved by utilizing a multi-horizon tree formulation, in which here-and-now operational decisions are decoupled from future investment and operational decisions.

The case study presented illustrates the use of EMPIRE for a European decarbonization study. Driven by the EU ETS price from the European reference case 2013 an emission reduction of more than 80 % is achieved displacing unabated fossil fuel generation with onshore wind and CCS. By allowing interconnector expansion, more wind power was deployed, which significantly reduces the system operational costs. However only small differences are observed for the total emissions.

There are two natural extensions to the work presented here. Firstly, the current version of EMPIRE does not fully make use of the possibilities of the multi-horizon tree formulation. By incorporating strategic uncertainty, which could for instance affect technology costs, fuel price developments or carbon price development, the effect of long-term uncertainty on decarbonization pathways can be addressed. The second extension of the work is to develop algorithms for efficient solution of multi-horizon models. In particular decomposition methods, such as Benders Decomposition, mixed with parallel computing is a possible approach. By reducing computation times, and distributing computation tasks, it would be possible to considerably increase the number of stochastic operational scenarios used and get a better representation of the variability associated with intermittent renewables. For the levels of wind deployment seen in the illustration cases presented in this paper such considerations are extremely important for determining the need for operational flexibility in the system.

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A Nomenclature

Table 1: Paramters and variables in the EMPIRE model

Sets and indices		
Set	Index	Description
$\mathcal{N}$	n	Nodes (country)
$\mathcal{G}$	g	Generators
$\mathcal{L}$	l	Interconnector links (unidirectional)
$\mathcal{A}$	a	Arcs (for directional flow)
$\mathcal{B}$	b	Storages
$\mathcal{H}$	h	Operational hour ($\mathcal{H}^- = \mathcal{H} \setminus \{1\}$), $\lvert\mathcal{H}\rvert = H$
$\mathcal{S}$	s	Season
$\mathcal{I}$	i	Investment time period, $\lvert\mathcal{I}\rvert = I$
Ω	ω	Stochastic scenario, $\lvert\Omega\rvert = O$
$\mathcal{T}$	t	Aggregated generator technologies
$\mathcal{K}$	k	Years for historical data profiles
Decision variables		
Symbol	Description	
x^{gen}_{gi}	Generation capacity investment	
x^{tran}_{li}	Line capacity investment	
x^{storPW}_{bi}	Storage power capacity investment	
x^{storEN}_{bi}	Storage energy capacity investment	
$y^{\text{gen}}_{ghi\omega}$	Generation	
$y^{\text{flow}}_{ahi\omega}$	Line flow	
$y^{\text{chrg}}_{bhi\omega}$	Storage charge	
$y^{\text{dischrg}}_{bhi\omega}$	Storage discharge	
$y^{\text{LL}}_{nhi\omega}$	Energy not supplied (load shed)	
$w^{\text{stor}}_{bhi\omega}$	Storage energy content. Charge level = $w^{\text{stor}}_{bhi\omega}/v^{\text{storEN}}_{bi}$	
v^{gen}_{gi}	Installed generation capacity	
v^{tran}_{li}	Installed transmission capacity	
v^{storPW}_{bi}	Installed storage power capacity	
v^{storEN}_{bi}	Installed storage energy capacity	
Parameters		
Symbol	Description	

Continued on next page

Table 1 – *Continued from previous page*

r	Discount rate
ϑ	Five year scale factor, $\vartheta = \sum_{j=0}^{4}(1+r)^{-j} = \frac{(1+r)^5-1}{r(1+r)^4}$
π_ω	Scenario probability, $\sum_{\omega\in\Omega}\pi_\omega = 1$, $0 \leq \pi_\omega \leq 1$.
α_s	Seasonal scale factor
c_{gi}^{gen}	Generator investment cost
c_{li}^{tran}	Transmission investment cost
c_{bi}^{storPW}	Storage power capacity investment cost
c_{bi}^{storEN}	Storage energy capacity investment cost
q_{gi}^{gen}	Generator short-run marginal cost
q_{ni}^{voll}	Value of lost load at node
$\xi_{nhi\omega}^{\text{load}}$	Load
$\xi_{ghi\omega}^{\text{gen}}$	Generator capacity availability
$\xi_{gsi\omega}^{\text{RegHydroLim}}$	Max energy production from regulated hydro
$\xi_{ni\omega}^{\text{HydroLim}}$	Max energy production from hydro at node
τ_{*hk}^{type}	Historical data series (type and $*$ indicate data profile type)
$\overline{x}_{gi}^{\text{gen}}$	Initial generation capacity
$\overline{x}_{li}^{\text{tran}}$	Initial transmission capacity
$\overline{x}_{bi}^{\text{storPW}}$	Initial storage power capacity
$\overline{x}_{bi}^{\text{storEN}}$	Initial storage energy capacity
$\overline{X}_{ti}^{\text{gen}}$, $\overline{V}_{ti}^{\text{gen}}$	Generation max build/install capacity (aggregate technology)
$\overline{X}_{li}^{\text{tran}}$, $\overline{V}_{li}^{\text{tran}}$	Transmission max build/install capacity
$\overline{X}_{bi}^{\text{storPW}}$, $\overline{V}_{bi}^{\text{storPW}}$	Storage power capacity max build/install capacity
$\overline{X}_{bi}^{\text{storEN}}$, $\overline{V}_{bi}^{\text{storEN}}$	Storage energy capacity max build/install capacity
i_{*}^{life}	Life time for investment ($*$ used as a wild-card for g, l, b)
η_l^{tran}	Linear line efficiency. Loss $= 1 - \eta_l^{\text{tran}}$
η_b^{chrg}	Storage charge efficiency
η_b^{dischrg}	Storage discharge efficiency
$\eta_b^{\text{roundtrip}}$	Storage round-trip efficiency, $\eta_b^{\text{roundtrip}} = \eta_b^{\text{chrg}}\eta_b^{\text{dischrg}}$
γ_g^{gen}	Generator ramp-up capability
ρ_b	Storage discharge to charge power capacity ratio
β_b	Storage power to energy capacity ratio

B Pre-processing of EMPIRE parameters

B.1 Calculation of short-run marginal cost parameters

The variable operational costs of a particular type of technology can typically be split into separate components associated different parts of the power plant operation. A generic example, assuming internalization of emission costs, is

$$\begin{aligned}\text{Variable costs} &= \text{Fuel costs} + \text{Variable operation and maintenance costs}\\ &+ \text{Carbon emission cost} + \text{Carbon transport and storage costs}\end{aligned}$$

EMPIRE use linear cost functions, based on average heat rates, for all generators as seen in the objective function. The coefficient of the generator production output variables can therefore be

Table 2: List and description of parameters used to calculate the generation cost coefficients.

Symbol	Dimension	Description
hr_{ti}	GJ_{th}/MWh_e	Heat rate (note: $h = 3.6/\text{efficiency}$)
p^{F}_{fi}	€$/GJ_{th}$	Price of fuel
p^{C}_{i}	€$/tCO_2$	Carbon emission price (tax or EUA)
rf^{ccs}_{ti}		CCS removal fraction
e_f	tCO_2/GJ_{th}	Carbon content of fuel
$c^{vO\&M}_{ti}$	€$/MWh_e$	Variable operation and maintenance cost
$c^{ccsT\&S}_{ti}$	€$/tCO_2$	Carbon storage and transport cost
q^{gen}_{gi}	€/MWh	Marginal cost of generation (SRMC)

interpreted as the short-run marginal cost of production. In year $i \in \mathcal{I}$, for a generator $g \in \mathcal{G}$ of technology $t \in \mathcal{T}$ using fuel $f \in \mathcal{F}$ be parameterized as

$$q^{\text{gen}}_{gi} = h_{ti} \cdot p^{\text{F}}_{fi} + c^{\text{vO\&M}}_{ti} + h_{ti} \cdot (1 - rf^{\text{ccs}}_{ti}) \cdot e_f \cdot p^{\text{C}}_{i} + h_{ti} \cdot rf^{\text{ccs}}_{ti} \cdot e_f \cdot c^{\text{ccsT\&S}}_{ti}. \tag{7}$$

An overview of the symbols used can be found in Table 2.

For conventional thermal generation burning fossil fuel no carbon is captured and stored which means $rf^{\text{ccs}}_{ti} = 0$. The variable cost expression therefore reduces to

$$q^{\text{gen}}_{gi} = hr_{ti} \cdot p^{\text{F}}_{fi} + c^{\text{vO\&M}}_{ti} + hr_{ti} \cdot e_f \cdot p^{\text{C}}_{i}. \tag{8}$$

For nuclear power the assumed fuel carbon contents is assumed zero, i.e. $e_f = 0$, yielding variable cost

$$q^{\text{gen}}_{gi} = hr_{ti} \cdot p^{\text{F}}_{fi} + c^{\text{vO\&M}}_{ti}. \tag{9}$$

For renewable technologies $p^{\text{F}}_{fi} = 0$ and $e_f = 0$, which leaves the variable cost simply equaling the operation and maintenance cost

$$q^{\text{gen}}_{gi} = c^{\text{vO\&M}}_{ti}. \tag{10}$$

B.2 Pre-processing baseline data series

Table 3 gives an overview of the symbols used in this section. The baseline data series for hydro power production and load, obtained using the scenario generation routine discussed in the main article, were further transformed before being used as input to EMPIRE. The normalized production profiles for wind power and solar PV production were used directly. The following shows how the baseline series where used in EMPIRE

- Onshore and offshore wind power production and solar PV production:

$$\xi^{\text{gen}}_{ghi\omega} = \xi^{\text{gen}}_{gh0\omega}, \quad h \in \mathcal{H}, g \in \mathcal{G}^{\text{intermittent RES}}, i \in \mathcal{I}, \omega \in \Omega.$$

  Note: The underlying data series used to generate $\xi^{\text{gen}}_{gh0\omega}$ for renewable generators are normalized production profiles. Therefore the baseline data series are also normalized production values and can be used directly as input to EMPIRE.

Table 3: List and description of parameters processed after using the scenario generation routine.

Symbol	Description
$\mathcal{N}$	Set of nodes (country)
$\mathcal{G}$	Set of generators (superscript used to identify technology type)
$\mathcal{H}$	Set of operational hours
$\mathcal{S}$	Set of seasons
$\mathcal{I}$	Set of investment time periods
Ω	Set of stochastic scenarios
π_ω	Stochastic scenario probability
α_s	Seasonal scale factor
e_{0n}	Annual demand in base year (historical)
e_{in}	Annual demand for given investment period (target)
$\xi^{\text{type}}_{*h0\omega}$	Baseline data series (output from scenario generation)
$\xi^{\text{load}}_{nhi\omega}$	Load
$\xi^{\text{gen}}_{ghi\omega}$	Generator capacity availability
$\xi^{\text{RegHydroLim}}_{gsi\omega}$	Max energy production from regulated hydro

- Regulated hydro power production:

$$\xi^{\text{RegHydroLim}}_{gsi\omega} = \sum_{h\in\mathcal{H}_s} \xi^{\text{gen}}_{hg0\omega}, \quad g \in \mathcal{G}^{\text{RegHydro}}, s \in \mathcal{S}, i \in \mathcal{I}, \omega \in \Omega.$$

  Note: The underlying data series used to generate $\xi^{\text{gen}}_{*h0\omega}$ for regulated hydroelectric generators are (synthetic) hourly production data. Summing these values over a time interval will therefore yield the total energy produces during this time.

- Load data series: In order to reflect development in demand for electricity from one investment period to another the baseline load series are EMPIRE subject to a linear transformation of the baseline data. For investment period $i \in \mathcal{I}$ assume that the target annual demand for electricity in node $n \in \mathcal{N}$ is e_{in}. The annual demand based on the baseline profile data is denoted e_{0n}. The actual demand data used in EMPIRE is then computed as

$$\xi^{\text{load}}_{nhi\omega} = \xi^{\text{load}}_{nh0\omega} + \frac{e_{in} - e_{0n}}{8760}, \quad h \in \mathcal{H}, n \in \mathcal{N}, i \in \mathcal{I}, \omega \in \Omega.$$

  The new series have the desired annual demand since (for $n \in N$ and $i \in \mathcal{I}$)

$$\sum_{\omega\in\Omega} \pi_\omega \sum_{s\in\mathcal{S}} \alpha_s \sum_{h\in\mathcal{H}_s} \xi^{\text{load}}_{nhi\omega} = \underbrace{\sum_{\omega\in\Omega} \pi_\omega \sum_{s\in\mathcal{S}} \alpha_s \sum_{h\in\mathcal{H}_s} \xi^{\text{load}}_{nh0\omega}}_{=e_{0n}} + \underbrace{\sum_{\omega\in\Omega} \pi_\omega}_{=1} \underbrace{\sum_{s\in\mathcal{S}} \alpha_s \sum_{h\in\mathcal{H}_s}}_{=8760} \frac{e_{in} - e_{0n}}{8760},$$
$$= e_{in}.$$

C Input data documentation

C.1 Data sources

The input data used by EMPIRE has been collected from multiple sources. Hourly load time series for all countries in the model come from the ENTSO-E data portal (ENTSO-E, 2012).

Also net transfer capacities for cross-border exchange are based on ENTSO-E data. Normalized production profiles for wind and solar generation for every country have been provided by the same data material as was used by the EU funded project SUSPLAN (de Joode et al., 2011). Investment costs and generation technology specifications are provided exclusively from members of ZEP's market economics group II and is documented in ZEP (2013). Initial generator technology installed capacity data are collected, and consolidated, from a number of different sources including ENTSO-E, EURELECTRIC, EUR'Observer, NREAP and the following ISO and market operator's websites: National Grid, Red Elèctrica, Terna, EEX.

C.2 Renewable energy potential

For renewable generation technologies the maximum installed capacities are constrained by land-area available for deployment. For solar PV we assume that capacity per area unit is 150 W/m^2, and we limit the total deployment of PV panels to cover at most 14 % of a country's total land-area. For onshore wind the capacity to area ratio is assumed to be 7 MW/km^2, and the maximum installed capacity is based on limiting the total area use to 5 % of each country's agricultural land-area. Wind offshore maximum capacity limits are based on the high wind scenario published in the final report from the EU funded project TradeWind (2009). For coal and lignite we constrain the installed capacity to the maximum number found for each country in the report EURELETRIC (2011) (plus a 10 % margin). The same applies for nuclear power.

D Input data for used for EMPIRE

Table 4: Investment cost for generation technologies, in €$_{2010}$/kW. Source (ZEP, 2013).

	2010	2015	2020	2025	2030	2035	2040	2045	2050
Lignite	1600	1600	1600	1600	1600	1600	1600	1600	1600
Lignite CCS				2600	2530	2470	2400	2330	2250
Coal	1500	1500	1500	1500	1500	1500	1500	1500	1500
Coal CCS				2500	2430	2370	2300	2230	2150
Gas OCGT	400	400	400	400	400	400	400	400	400
Gas CCGT	650	650	650	650	680	710	740	770	800
Gas CCS				1350	1330	1310	1290	1270	1250
Bio 10pcnt cofir.	1600	1600	1600	1600	1600	1600	1600	1600	1600
Bio 10pcnt cofir. CCS				2600	2530	2470	2400	2330	2250
Nuclear	3000	2838	2675	2513	2350	2188	2025	1863	1700
Wave	6050	5669	5288	4906	4525	4144	3763	3381	3000
Geo	5500	5500	5500	5500	5500	5500	5500	5500	5500
Hydro regualted	3000	3000	3000	3000	3000	3000	3000	3000	3000
Hydro run-of-river	4000	4000	4000	4000	4000	4000	4000	4000	4000
Wind onshore	1200	1188	1175	1163	1150	1138	1125	1113	1100
Wind offshore	4080	3930	3780	3630	3480	3330	3180	3030	2880
Solar PV	1900	1788	1675	1563	1450	1338	1225	1113	1000

Table 5: Fixed operation and maintenance costs, in €$_{2010}$/kW/an. Source (ZEP, 2013).

	2010	2015	2020	2025	2030	2035	2040	2045	2050
Liginite exist	32	32	32	32	32	32	32	32	32
Lignite	32	32	32	32	32	32	32	32	32
Lignite CCS				51	50	49	47	46	45
Coal exist	31	31	31	31	31	31	31	31	31
Coal	31	31	31	31	31	31	31	31	31
Coal CCS				47	46	45	44	43	41
Gas exist	20	20	20	20	20	20	20	20	20
Gas OCGT	20	20	20	20	20	20	20	20	20
Gas CCGT	30	30	30	30	35	40	45	49	54
Gas CCS				47	50	54	58	61	65
Oil exist	20	20	20	20	20	20	20	20	20
Bio exist	48	47	46	45	44	43	42	41	40
Bio 10pcnt cofir.	32	32	32	32	32	32	32	32	32
Bio 10pcnt cofir. CCS				51	50	49	47	46	45
Nuclear	134	131	127	123	120	116	112	108	105
Wave	154	154	154	154	154	154	154	154	154
Geo	92	92	92	92	92	92	92	92	92
Hydro regualted	125	125	125	125	125	125	125	125	125
Hydro run-of-river	125	125	125	125	125	125	125	125	125
Wind onshore	54	54	53	52	51	50	49	48	47
Wind offshore	138	133	128	122	117	112	107	102	96
Solar PV	20	20	21	22	23	24	24	25	26

Table 6: Generator efficiency for thermal technologies, in percent. Source (ZEP, 2013).

	2010	2015	2020	2025	2030	2035	2040	2045	2050
Liginite exist	35	35	36	36	36	36	36	37	37
Lignite	43	44	45	45	46	47	47	48	49
Lignite CCS				37	39	40	41	42	43
Coal exist	37	38	38	38	38	38	39	39	39
Coal	45	46	46	47	47	47	48	48	49
Coal CCS				39	40	41	41	42	43
Gas exist	48	49	50	51	52	52	53	54	55
Gas OCGT	40	40	41	41	41	41	41	42	42
Gas CCGT	60	60	60	60	61	63	64	65	66
Gas CCS				52	54	56	57	58	60
Oil exist	38	38	38	38	38	38	38	38	38
Bio exist	38	38	39	39	39	39	39	40	40
Bio 10pcnt cofir.	45	46	46	47	47	47	48	48	49
Bio 10pcnt cofir. CCS				39	40	41	41	42	43
Nuclear	36	36	36	36	36	37	37	37	37

Table 7: Variable operation and maintenance (O& M) costs, in €$_{2010}$/MWh. Source (ZEP, 2013). The variable O& M costs for oil, bio, hydro, wind and solar are added to the fixed O& M costs and reported in Table 5.

	2010	2015	2020	2025	2030	2035	2040	2045	2050
Liginite exist	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48
Lignite	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48
Lignite CCS				3.28	3.28	3.28	3.28	3.28	3.28
Coal exist	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46
Coal	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46	0.46
Coal CCS				2.46	2.46	2.46	2.46	2.46	2.46
Gas exist	0.45	0.45	0.45	0.45	0.47	0.49	0.51	0.53	0.55
Gas OCGT	0.45	0.45	0.45	0.45	0.47	0.49	0.51	0.53	0.55
Gas CCGT	0.45	0.45	0.45	0.45	0.52	0.59	0.66	0.73	0.80
Gas CCS				1.85	1.92	1.99	2.06	2.13	2.20
Bio 10pcnt cofir.	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48	0.48
Bio 10pcnt cofir. CCS				3.28	3.28	3.28	3.28	3.28	3.28
Nuclear	1.80	1.75	1.70	1.65	1.60	1.55	1.50	1.45	1.40

Table 8: Transport and storage costs assumed for carbon capture and storage technologies, in €$_{2010}$/tCO_2.

	2025	2030	2035	2040	2045	2050
CCS T&S cost	19	18	17	15	14	13

Table 9: Derived short-run marginal costs for the various technologies, in €$_{2010}$/MWh. Omitted technologies have SRMC less than 1 €/MWh.

	2010	2015	2020	2025	2030	2035	2040	2045	2050
Liginite exist	9	9	26	32	38	44	56	68	81
Lignite	7	7	21	25	30	34	43	52	61
Lignite CCS				30	29	28	27	27	26
Coal exist	15	15	31	37	42	48	59	70	81
Coal	13	13	26	30	34	39	48	56	65
Coal CCS				35	34	33	32	32	31
Gas exist	30	29	36	39	41	44	49	55	60
Gas OCGT	36	36	44	48	52	55	63	71	79
Gas CCGT	24	24	30	33	35	37	42	46	50
Gas CCS				38	37	37	37	38	39
Oil exist	69	70	85	92	99	106	118	128	138
Bio exist	47	47	47	44	42	45	47	49	53
Bio 10pcnt cofir.	15	15	27	31	34	39	47	55	63
Bio 10pcnt cofir. CCS				37	35	34	32	31	30
Nuclear	7	8	8	8	8	8	9	9	10

Table 10: Interconnector expansion costs. Given in €$_{2010}$/MW/km. Based on (de Joode et al., 2011).

	2010	2015	2020	2025	2030	2035	2040	2045	2050
HV lines	719	719	662	662	604	604	604	604	604
HV cables	2769	2769	2769	2769	2160	2160	1551	1551	1551

Table 11: Initial capacities for the ten countries with the highest installed capacity in 2010, and the other countries aggregated, as assumed in EMPIRE. Numbers in GW. Italy also has 1 GW installed capacity of geothermal generation, but this has been omitted from the table for brevity. Data from a number of different sources including ENTSO-E, EURELECTRIC, EUR'Observer, NREAP and the following ISO and market operator's websites: National Grid, Red Elèctrica, Terna, EEX

	Liginite	Coal	Gas	Oil	Bio	Nuclear	Hydro		Wind		Solar PV
							regulated	run-of-river	onshore	offshore	
Others	26	19	41	11	7	23	26	18	19	2	12
Germany	21	27	23	10	8	12	1	3	38	2	38
France		8	11	9	1	63	14	8	9		6
Italy		20	47	8	2		9	5	9		18
Great Brit.		28	32	4	4	10	1	1	8	4	5
Spain		12	27	4	1	8	13	3	23		5
Sweden			1	4	3	10	10	7	5		
Poland	10	20	1						4		
Norway			1				22	6	1		
Netherlands		4	18	1					3		1
Romania	4	1	4		1		4	2	3		1
Europe	61	140	204	50	27	126	100	52	122	9	87

Table 12: Maximum installed capacity limits for the ten countries with the highest installed capacity in 2010, and the other countries aggregated, as assumed in EMPIRE. Numbers in GW. For Lignite and Coal the limit applies to the sum unabated and CCS capacity. Generation technologies using natural gas are not limited.

	Lignite	Coal	Nuclear	Hydro		Wind		Solar PV
				regulated	run-of-river	onshore	offshore	
Others	30	28	32	54	60	282	39	329
Germany	23	34		2	4	70	106	75
France		14	65	21	16	105	27	114
Italy		7		13	9	60	3	63
Great Brit.		48	17	7	3	53	68	51
Spain		12	12	40	10	88	22	106
Sweden		1	8	11	7	105	24	94
Poland	10	27	3	1	2	70		66
Norway				30	15	70	13	68
Netherlands		9	4			9	42	9
Romania	5	2	5	11	7	42	5	50
Europe	66	183	145	190	132	952	350	1024